

AI NMR Extraction for Spin-1 Signals

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Outline

- Polarization Extraction Methods (for ND_3)
- Neural Networks
- Preliminary results (for vector polarization)
- Tensor Polarization
- Observations & Outlook



Extracting Deuteron Polarization

- Can fit a signal by average the dependance on the azimuthal angle
 - $F_{\epsilon}(R, A, \eta) = \frac{2}{\pi} \int_0^{\pi/2} \frac{\sqrt{3} f_{\epsilon}(R, A, \eta, \phi)}{\sqrt{3 - \eta \cos(2\phi)}} d\phi \approx \frac{1}{J+1} \sum_{j=0}^J \frac{\sqrt{3} f_{\epsilon}(R, A, \eta, \phi)}{\sqrt{3 - \eta \cos(2\phi)}}, J = 64, 0 < \phi < 2\pi$
- Polarization Approximated as
 - $P = \frac{r^2 - 1}{r^2 + 1 + r}, \quad r = \frac{I_+}{I_-}$



Extracting Deuteron Polarization

- Thermal Equilibrium (TE)
 - When lattice (L-Helium) and the target material are at the same temperature, we have Boltzmann equilibrium $\rightarrow P_{TE} = \frac{4}{3} \tanh(\frac{\hbar\omega_d}{2kT})$
 - Assuming **linearity** of Q-Meter system, relationship between **area** and **polarization** is linear, i.e.,:
 - $P = C \int \frac{\omega_d S(\omega)}{\omega} = C P_{TE}$, where C is a calibration constant
 - NMR Signal: $S(\omega) = \Re\{V(\omega, \chi) - V(\omega, 0)\} \chi''(\omega)$, $\chi''(\omega)$ is the **absorption function** and $\chi(\omega)$ is the **magnetic susceptibility**



Extracting Deuteron Polarization

- TE method comes with considerable error ($\sim 4\%$ relative error but sometimes as much as **7%** for standard spin-1 fitting)
 - Error propagated from change in **area** of TE signal and fitted signal.
 - TE state takes **very long** to reach (can take several hours, ie ND3).
 - Dulya type fitting is prone to systematic errors and susceptible to signal-to-noise.
 - Dulya type fitting **not possible** for RF manipulated signal.



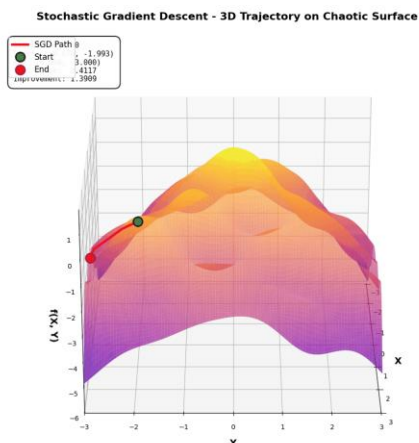
Q-Meter Limitations

- Sources of error:
 - $n\lambda/2$ cable length (Tuning errors)
 - Calibration Constant
 - Changes in RF environment
 - **Temperature Change**
 - **Statistical errors** dependent on DAQ



Artificial Neural Networks





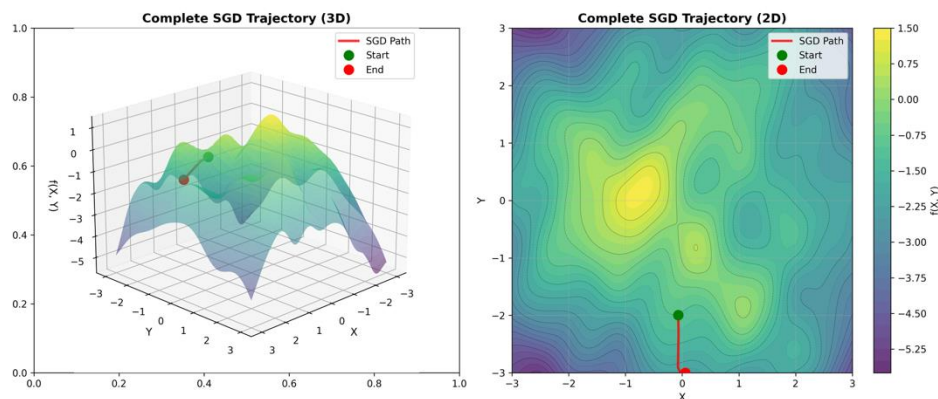
$$\hat{y} = Xw + b, \quad X, w \in \mathbb{R}^d$$

Loss Function: $L(w, b)$ (e. g., MSE, MAE)

Minimize: $(w^*, b^*) = \operatorname{argmin}(L(w, b))$

$$w \leftarrow w - \eta \sum_{i \in B} \partial_w L^{(i)}(w, b)$$

$$b \leftarrow b - \eta \sum_{i \in B} \partial_b L^{(i)}(w, b)$$



Goals

- (Reduce fit errors) **increase accuracy and precision** (for spin $\frac{1}{2}$ and 1)
- **Achieve reliable results** even with large range of noise and shifts
- Develop flexible software that improves reliability even when **working Q-meter outside its design specifications**
- Enable *real-time* polarization readings
- Apply to **ss-RF**/AFP type manipulations



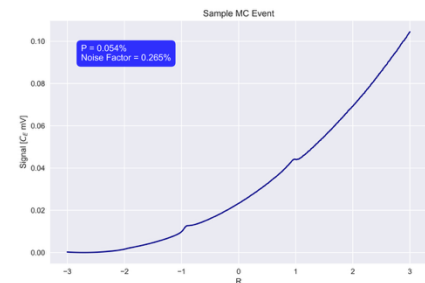
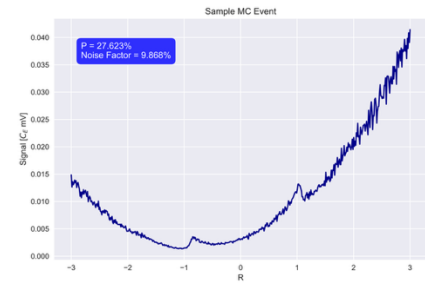
Why Neural Networks?

- Most Flexible ML approach to regression problems (UAT)
- Very fast inference is possible ($\sim$ ms scale updates with standard GPU)
 - More accurate real-time polarization monitoring
- Can do more with multidimensional information
- Common libraries help to leverage basic hardware



Data Generation

- Generated 1M data points varying over polarization and noise level (0% - 10% relative error per bin)
 - $SNR = \frac{|Max(Lineshape)|}{|Max(Noise)|}$
- Deuteron lineshape generated by analytical function
- Baseline simulated from Q-Meter circuitry parameters
 - U : Voltage
 - Z_{stray} : Stray capacitance
 - $C(\omega)$: Capacitance
 - I : Current
 - $\phi(\omega)$: Phase
 - η : Filling Factor (of coil)
 - $\lambda/2$: Cable length
- Data generated under various conditions of parameters to generalize



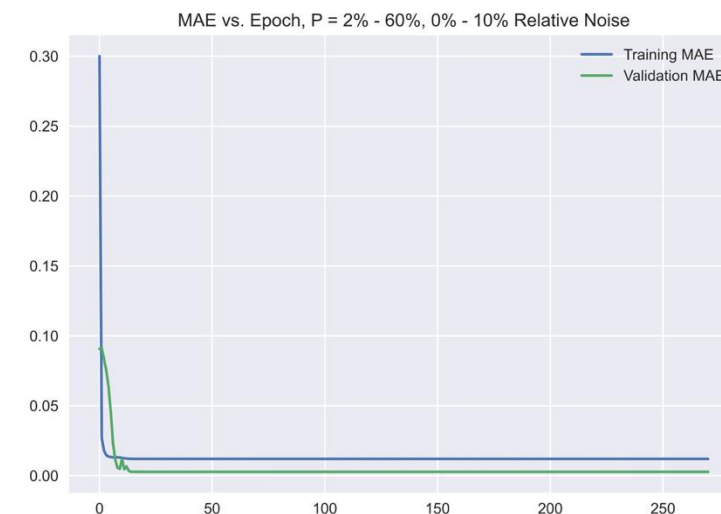
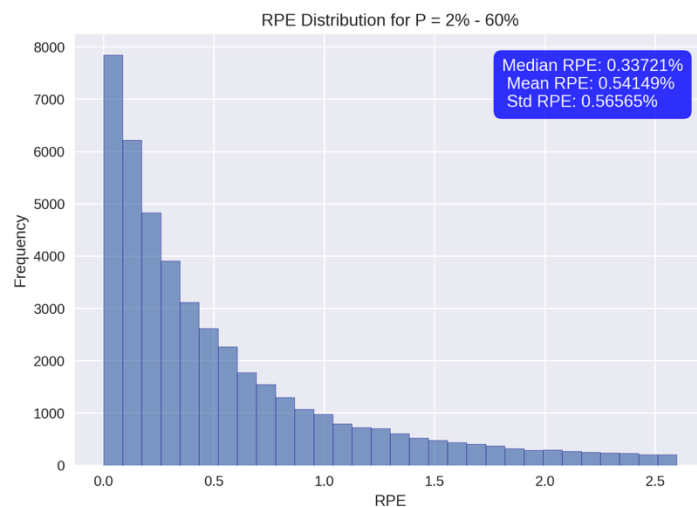
Preliminary Results



Results for $P = 2\% - 60\%$

Relative Error $\sim 0 - 10\%$ per bin

SNR $\sim 1-2$



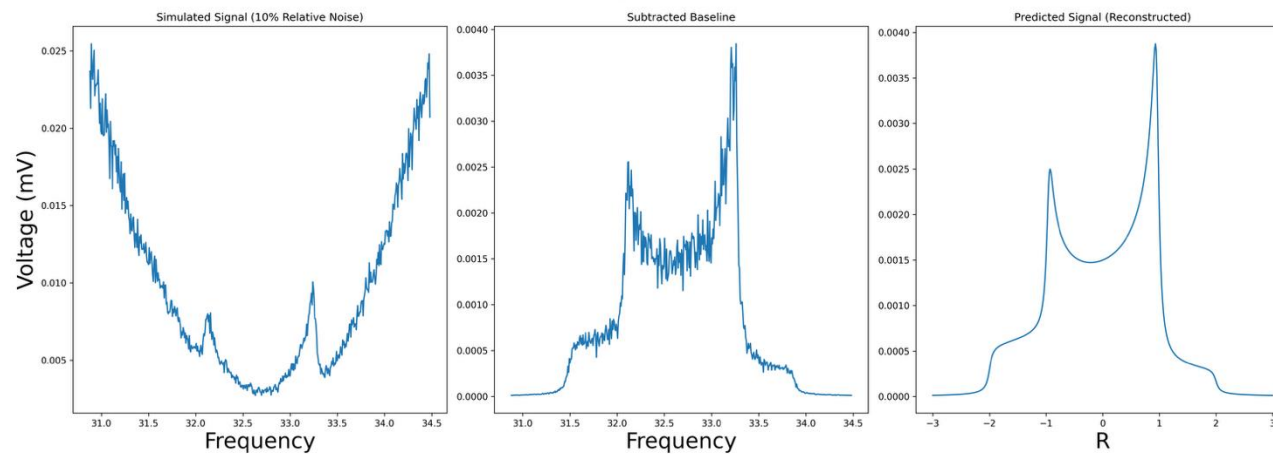
Median RPE: **0.34%**

Mean RPE: **0.54%**

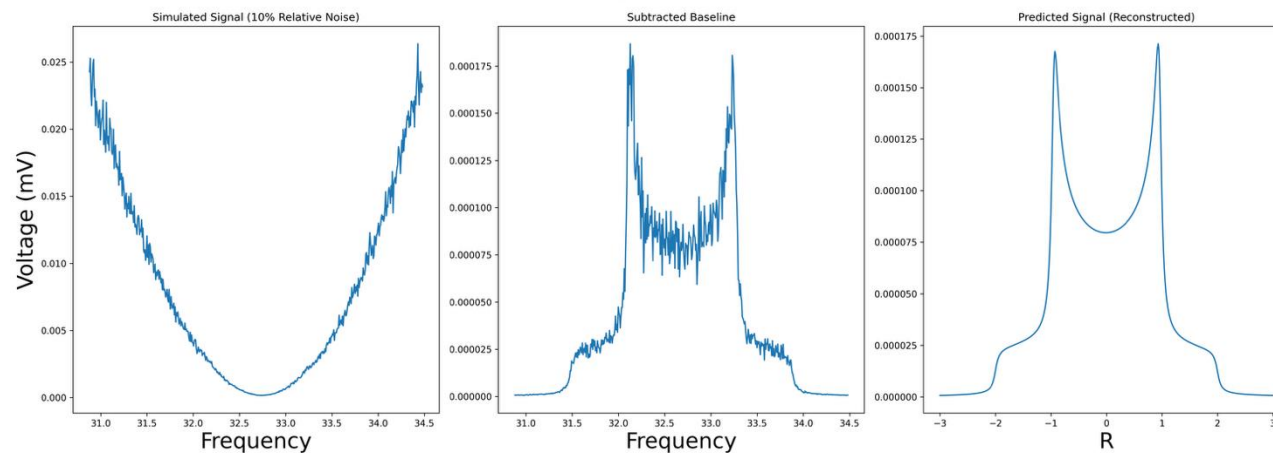
STD: **0.57%**



Simulated ($P = 41.47\%$) and Predicted ($P = 41.72\%$) Signal
RPE = 0.59%



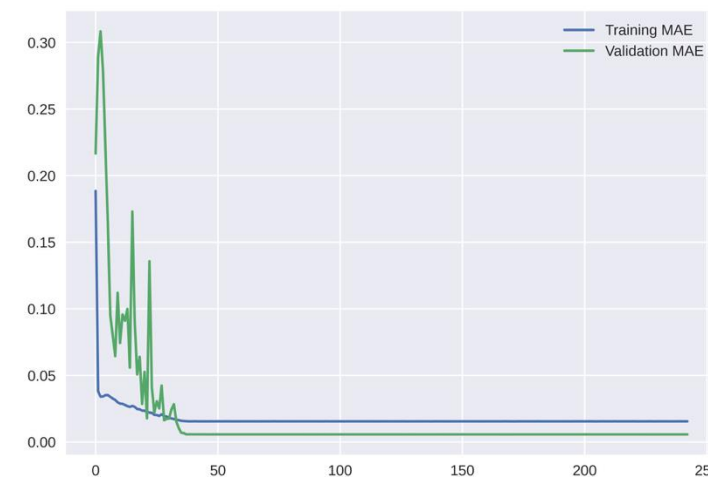
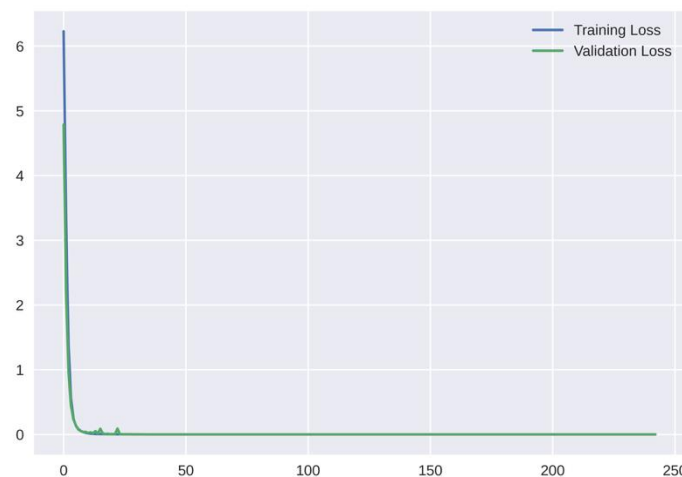
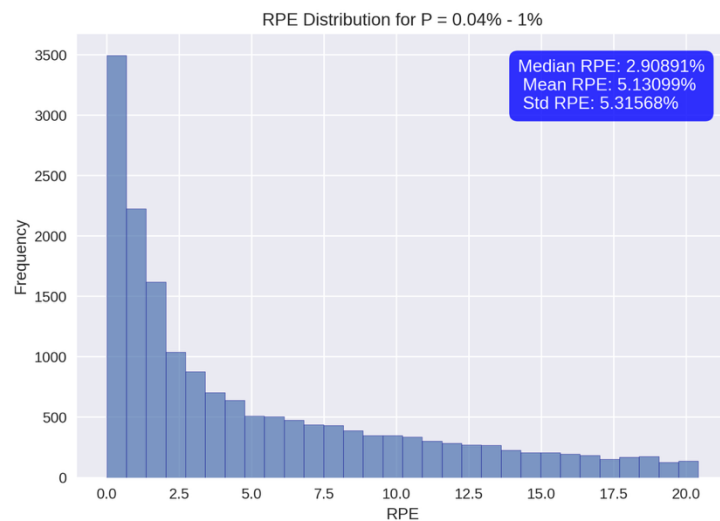
Simulated ($P = 2.219\%$) and Predicted ($P = 2.217\%$) Signal
RPE = 0.09%



Results for $P = 0.04\% - 2\%$

Relative Error $\sim 0 - 1\%$ per bin

SNR $\sim 1-2$



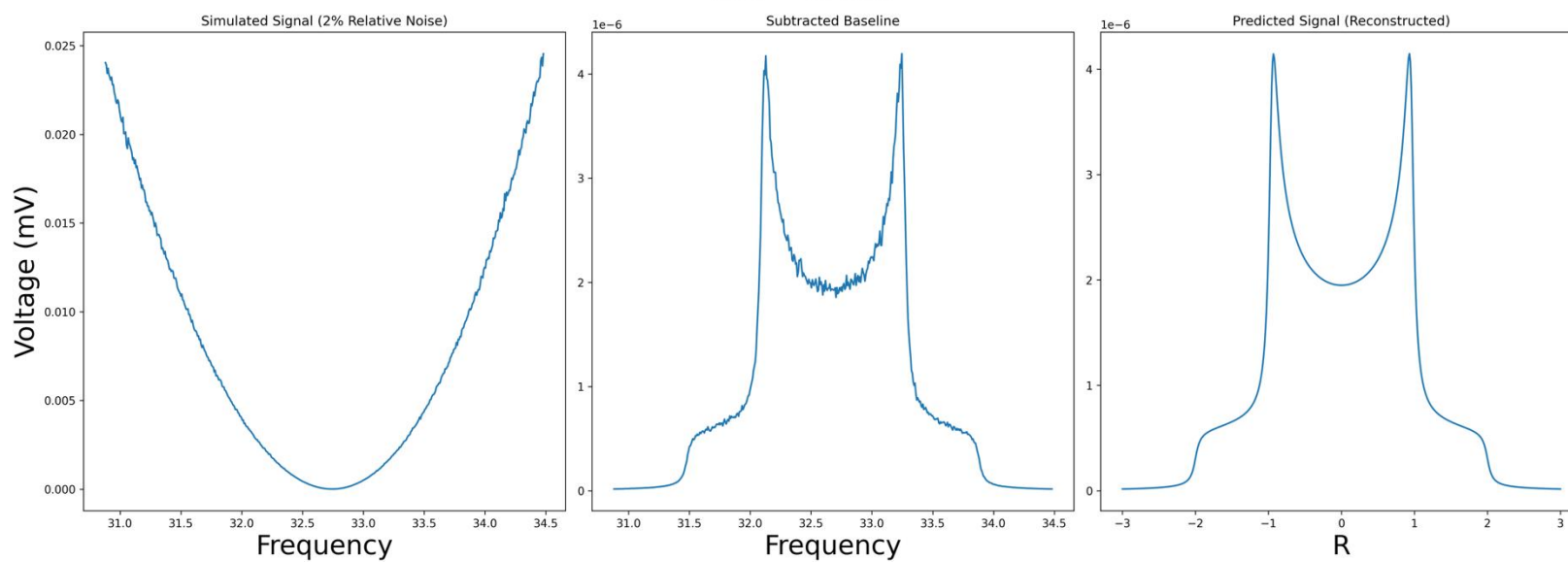
Median RPE: **2.9%**

Mean RPE: **5.13%**

STD: **5.32%**



Simulated ($P = 0.05402\%$) and Predicted ($P = 0.05425\%$) Signal
RPE = 0.43%

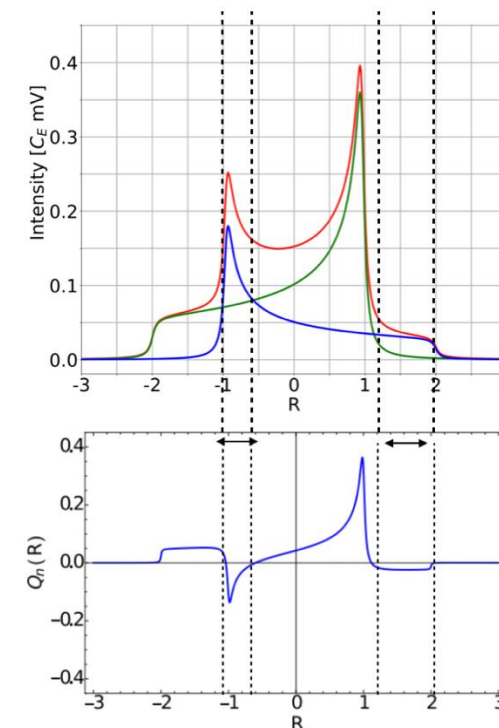
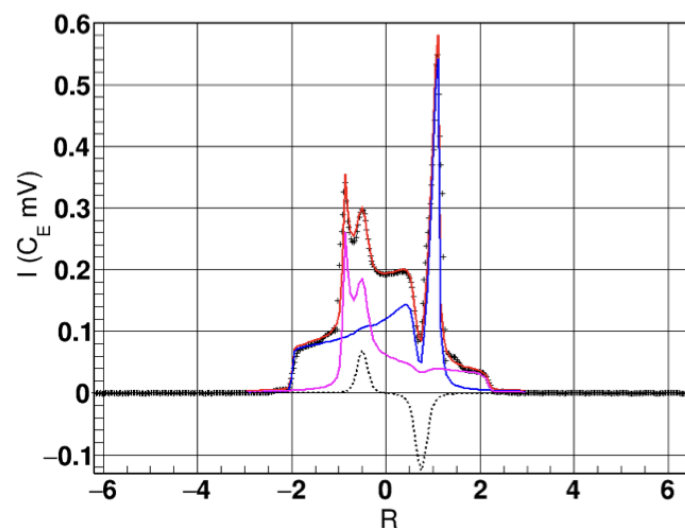
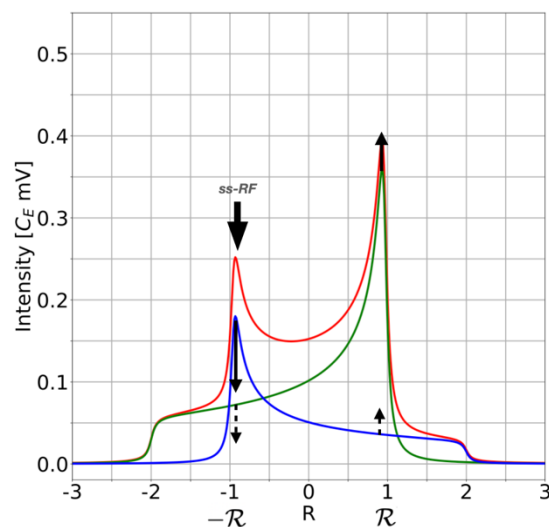


Tensor Polarization



Semi-Saturated Radiofrequency (ss-RF)

Relaxation Pathways



<https://arxiv.org/abs/1707.07065>



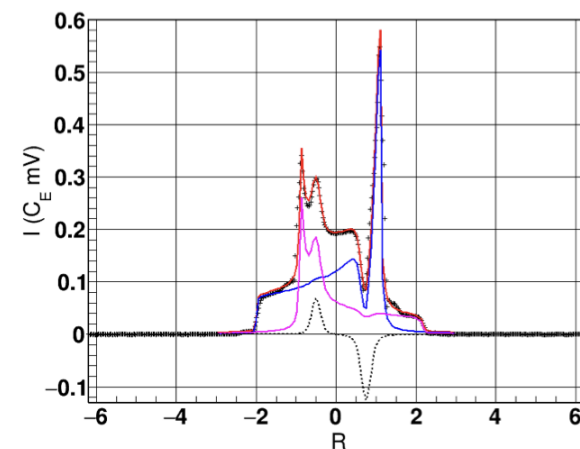
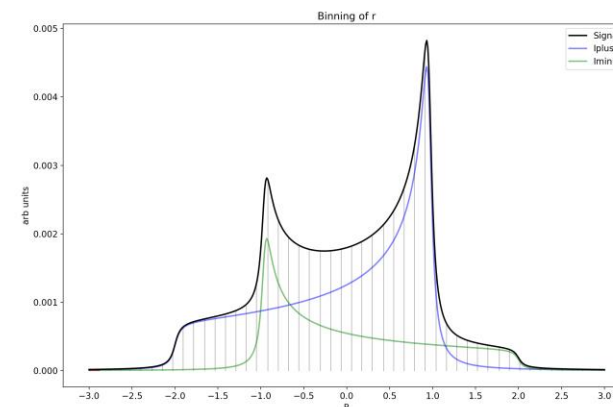
Principles of ss-RF

- Spin-Temperature Consistency
 - Hole burning locally erases non-equilibrium state biases by restoring partial equilibrium
 - Burning acts as *mirror image* of DNP, driving spin transition in **opposite** direction
- Differential Binning
 - Partitioning signal into frequency beams and manipulating/measuring each subset
- Rates Response
 - Peak achieved from hole burning is $\frac{1}{2}$ area of burned area (in high RF power limit)

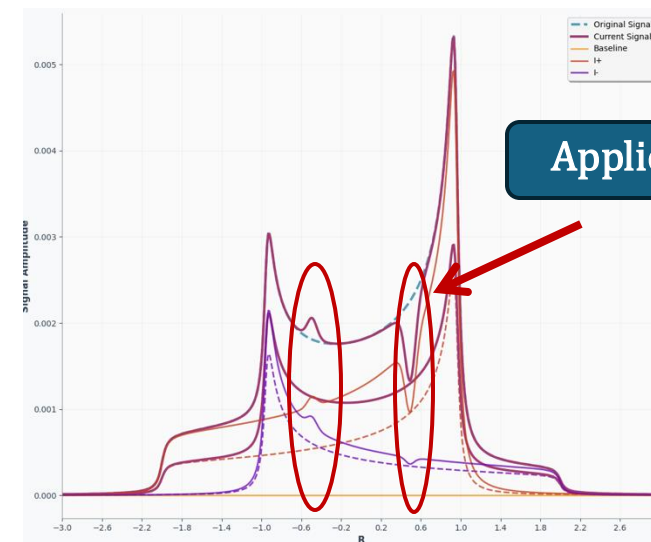
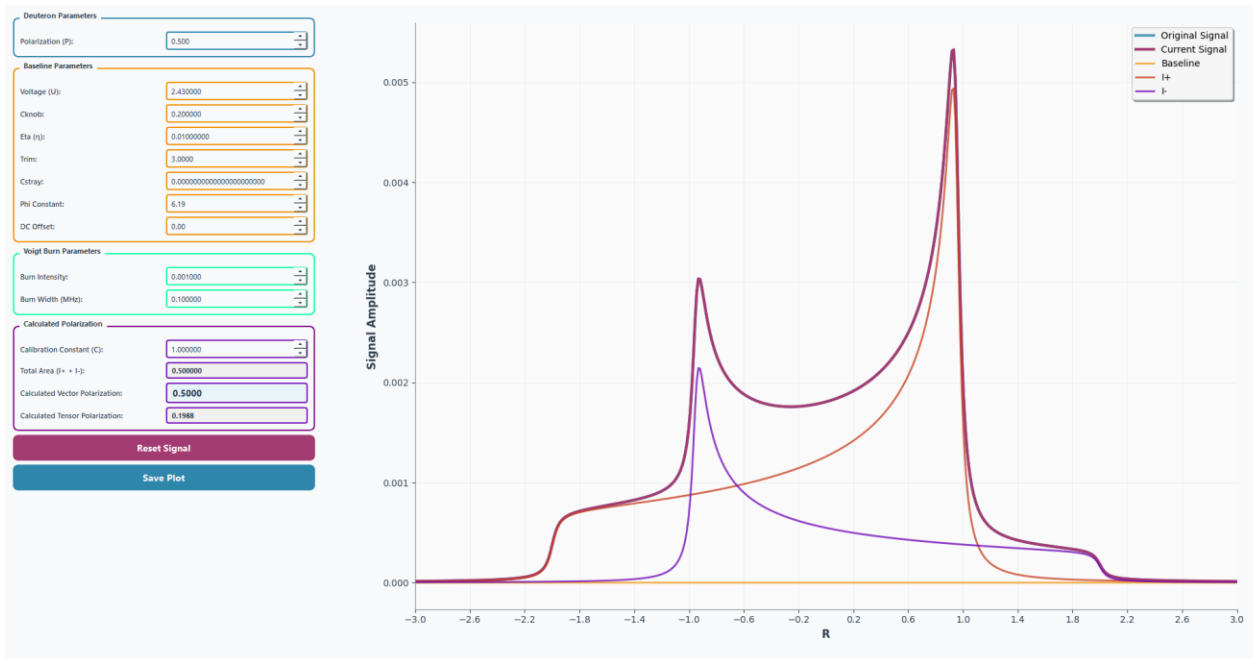
$$r = \frac{I_+}{I_-} \rightarrow r_i = \frac{I_{+,i}}{I_{-,i}}$$

$$P_i = C_i(I_{+,i} + I_{-,i})$$

$$P_{zz,i} = C_i(I_{+,i} - I_{-,i})$$



Burning Simulation



Calculated Vector Polarization:

0.4975

Calculated Tensor Polarization:

0.1990

Calculated Vector Polarization:

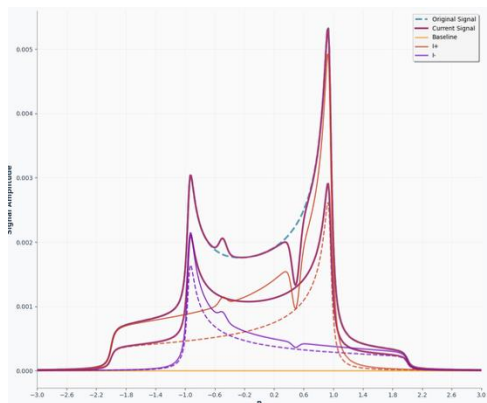
0.5000

Calculated Tensor Polarization:

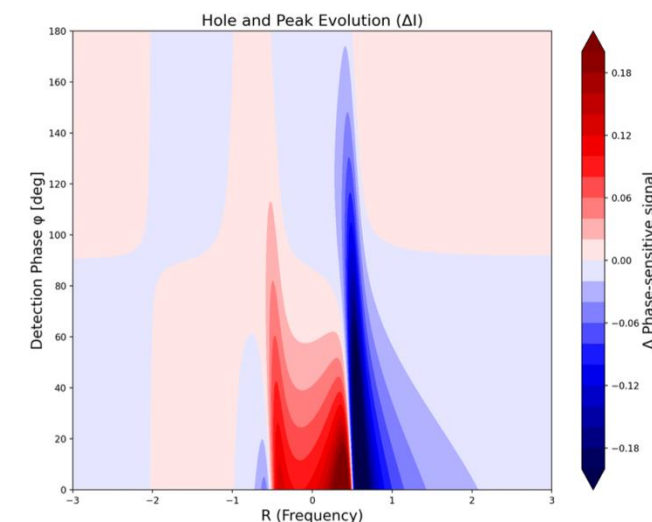
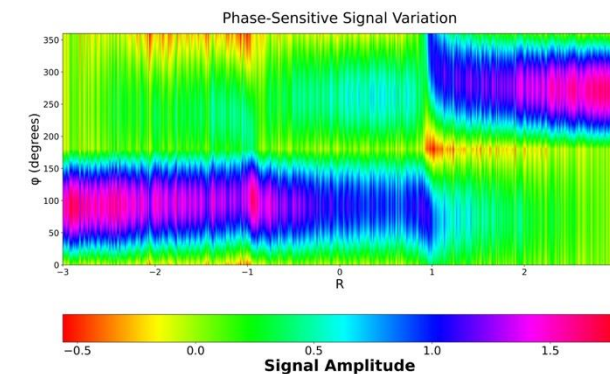
0.1988



Future Machine Learning Endeavors



- **1D Case:**
 - (bin P and P_{zz} in R domain only) to extract P and P_{zz} *invariantly* of RF manipulation
- **2D Case:**
 - Calculate P and P_{zz} along R *and* ϕ
 - → Train model with smaller, synchronized, phase-shifted tiemsteps
 - → *More information* to train on!

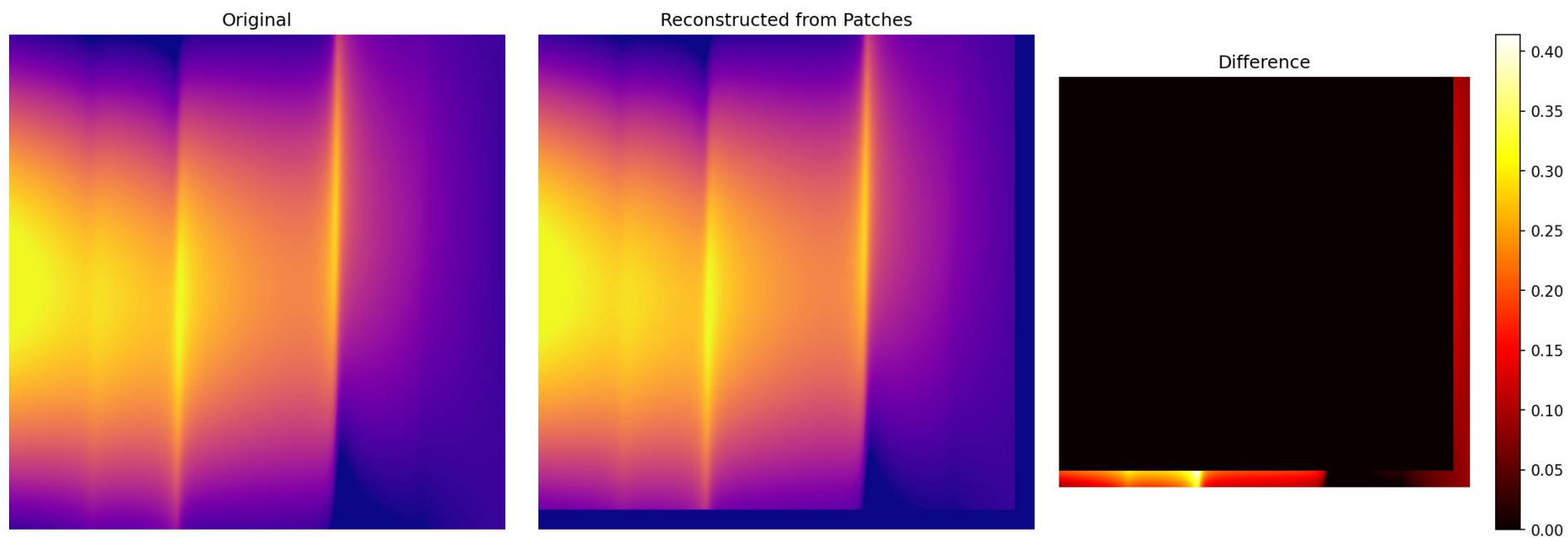


Thank you!

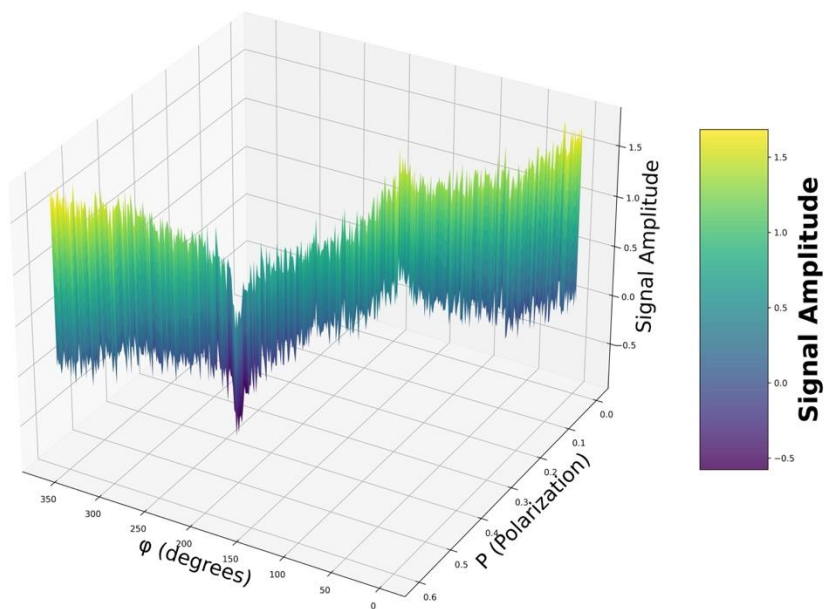


Leftovers





3D Signal Variation over R, ϕ , and P



3D Signal Variation over R, ϕ , and P

