

Enhancing Neutron Scattering Experimentation

A Data Science and Machine Learning Approach to Predict Background Scattering

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HAMLET
How to Apply Machine Learning to
Experimental & Theoretical

August 19 - 21, 2024
Copenhagen, Denmark
PHYSICS



EUROPEAN
SPALLATION
SOURCE



Master's Thesis:

Using McStas Union components to simulate a magnet sample environment & predicting background with machine learning



Kim Lefmann
Professor
NBI



Mads Bertelsen
Computational Neutron
Scattering Scientist
ESS, DMSC



Alex Holmes
Scientific Engineer
ESS

What's Neutron Scattering?

The ID of a Neutron

Spin	Charge	Magnetic Moment	Particle	Wave
1/2	0	$-1.9130 e\hbar/2m_p$	Yes	Yes

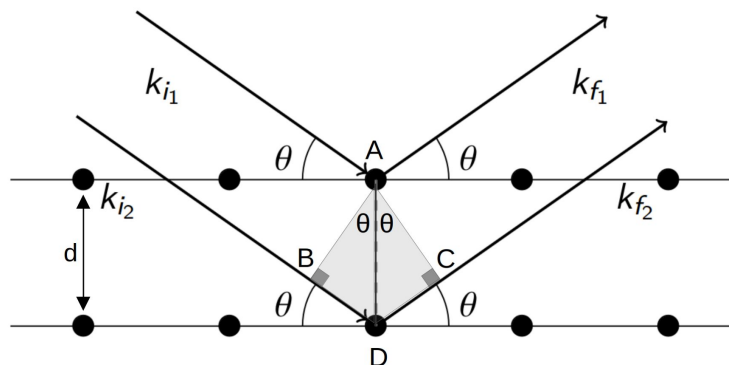
Interaction with matter

Absorption

Scattering

- Coherent & Incoherent
- Elastic & Inelastic

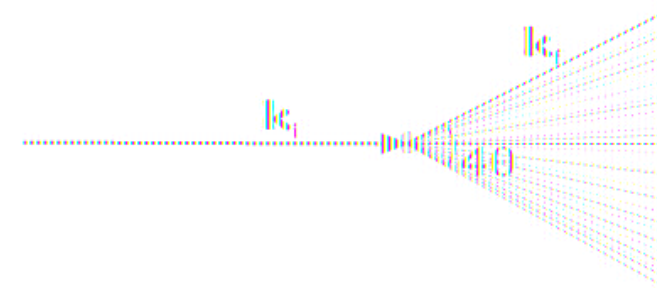
In Crystals



Bragg's Law

$$n\lambda = 2d \sin(\theta)$$

In Crystal Powders

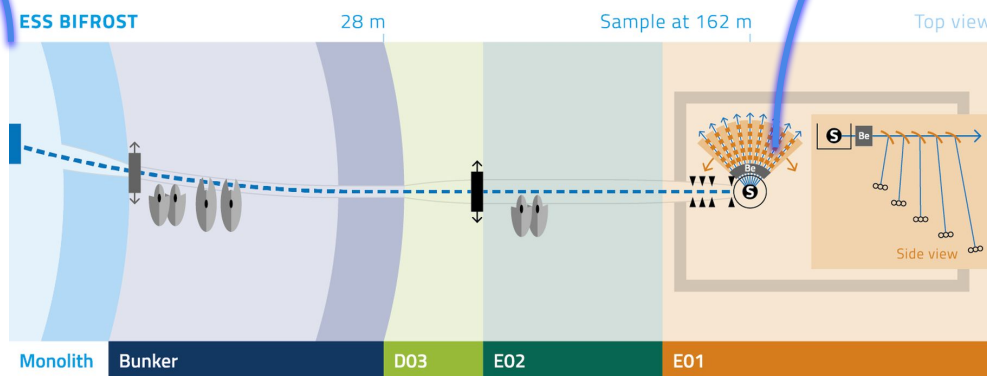
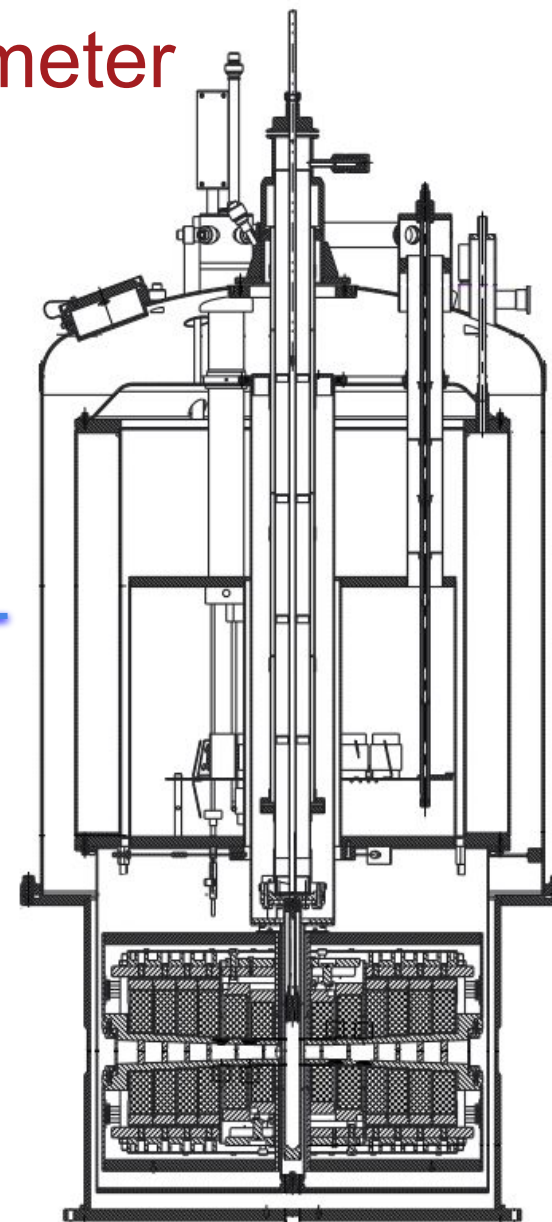


Debye-Scherrer
Cones

European Spallation Source - BIFROST Spectrometer

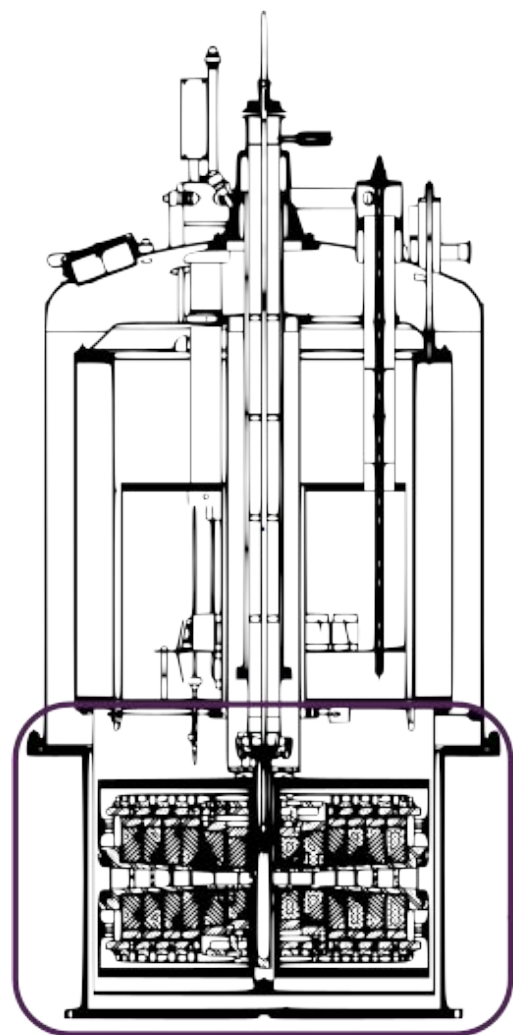


Sample Environment

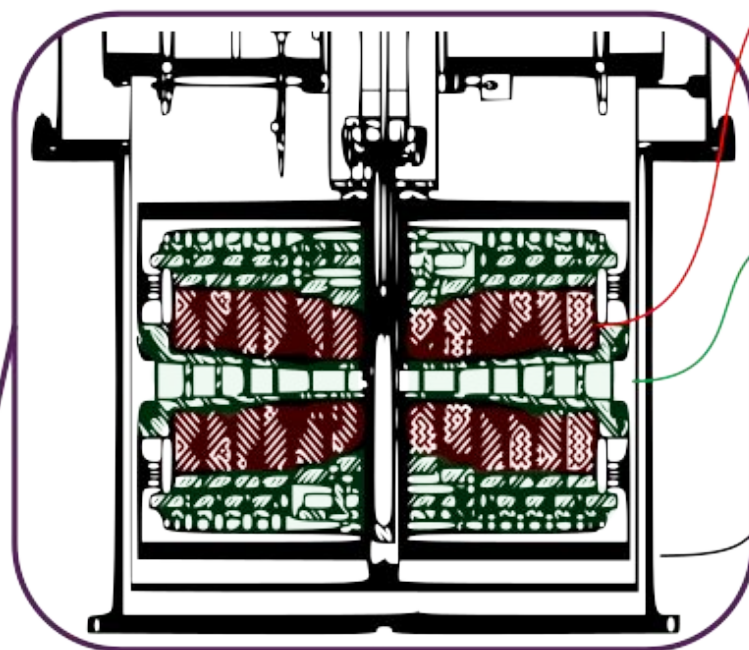


Creating synthetic data

Simulating the Sample Environment



Height	Largest diameter
1531 mm	721 mm
Beam path angle	Sample volume
$\pm 2^\circ$	1 cm ³



Magnet Coils

Add mass and large magnetic forces

Support structures

Withstand magnetic forces

Cryostats

Maintain conditions in the sample environment

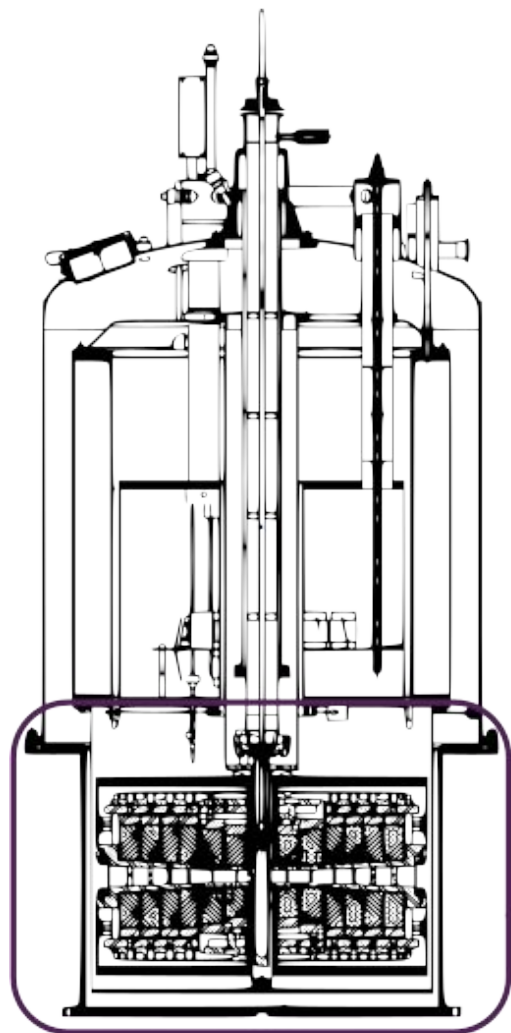
Monte Carlo Neutron Ray-Tracing Simulation Package



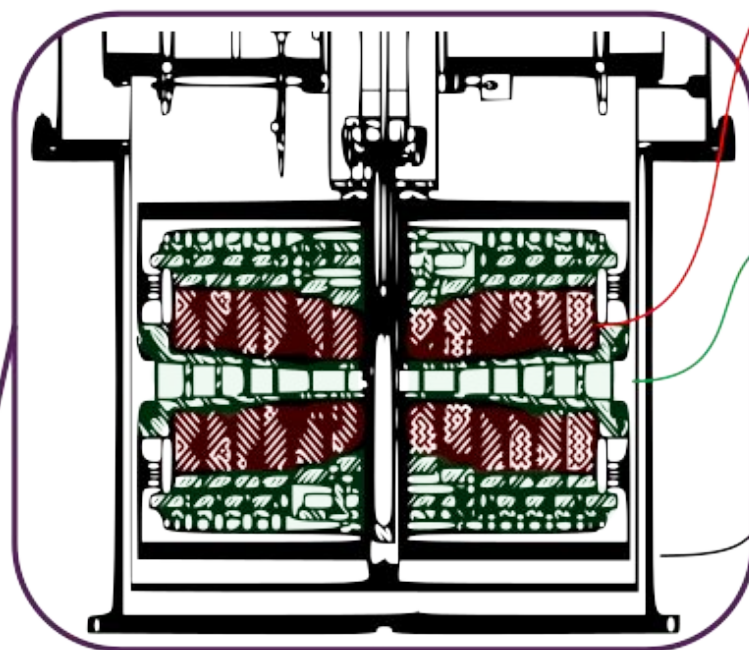
McStas Union

Assign physical properties to desired geometries

Simulating the Sample Environment



Height	Largest diameter
1531 mm	721 mm
Beam path angle	Sample volume
$\pm 2^\circ$	1 cm ³



Magnet Coils

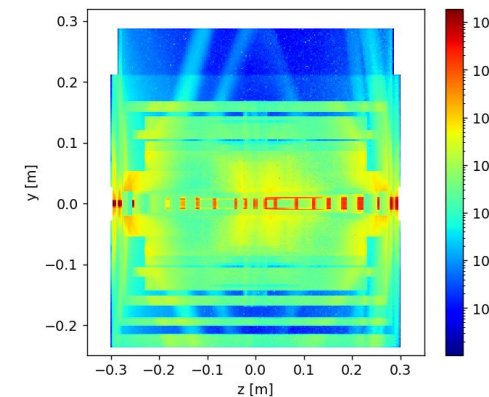
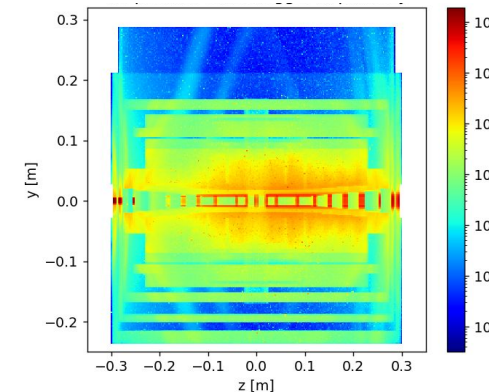
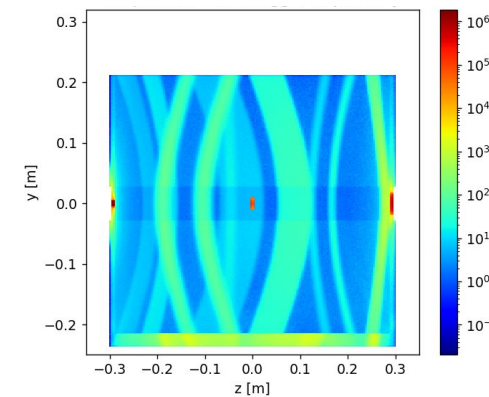
Add mass and large magnetic forces

Support structures

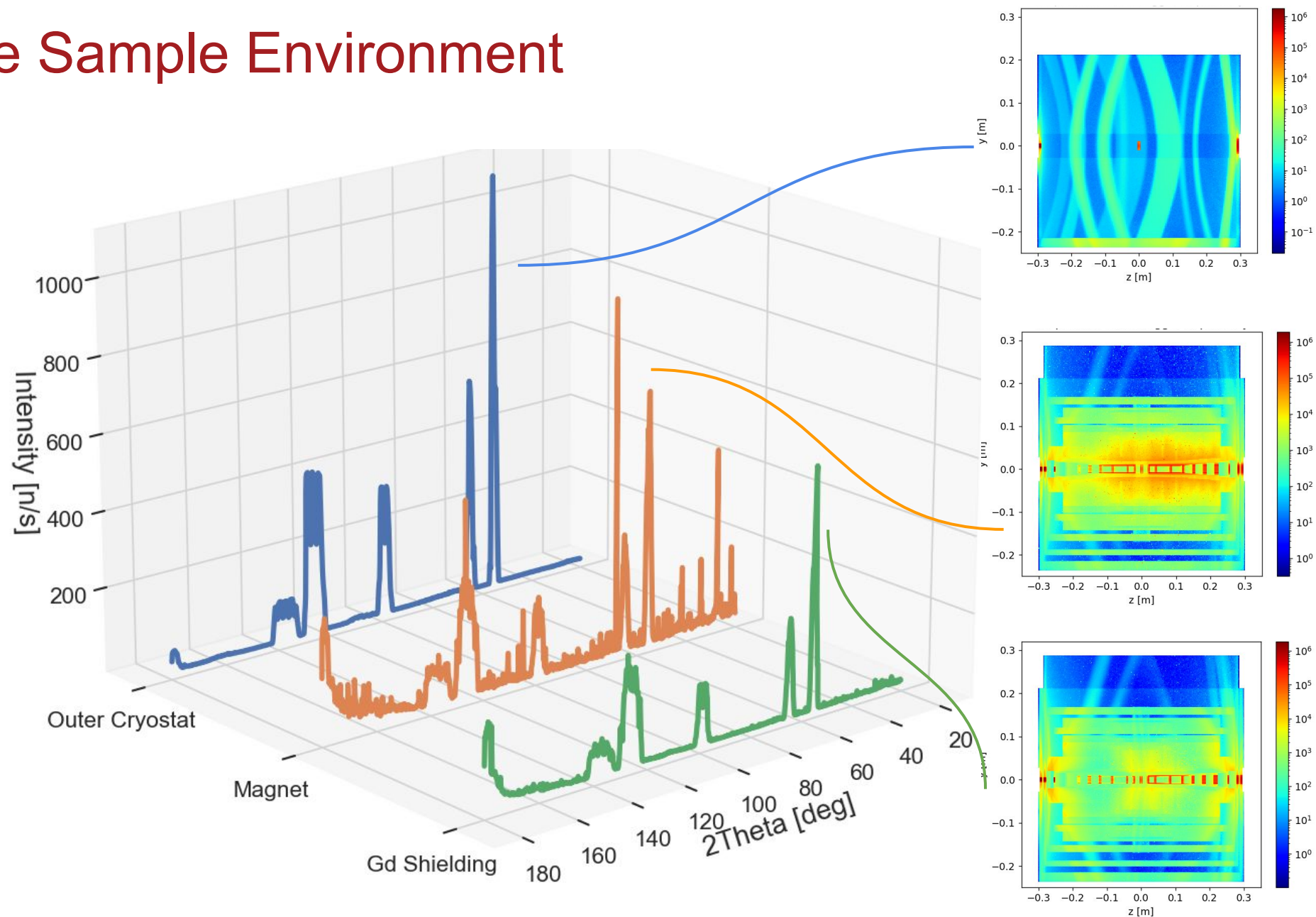
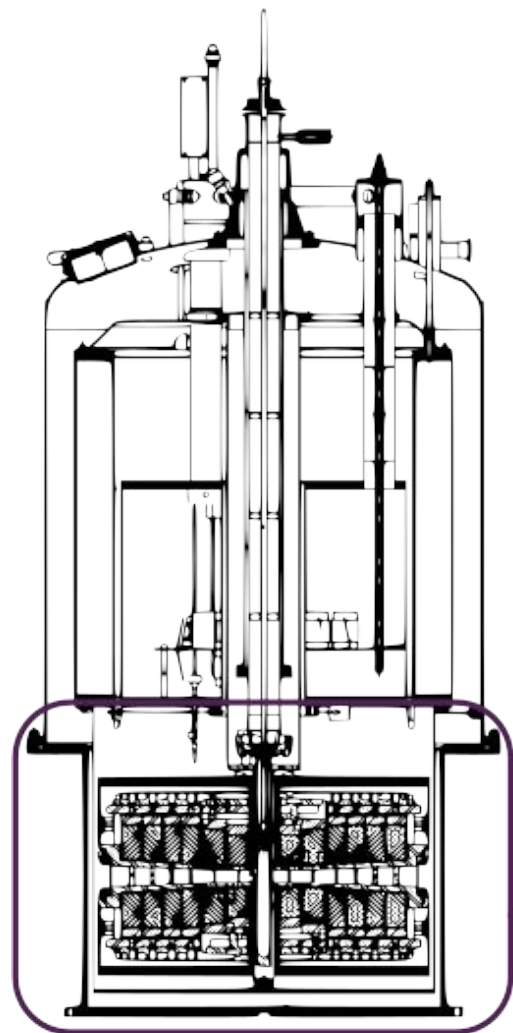
Withstand magnetic forces

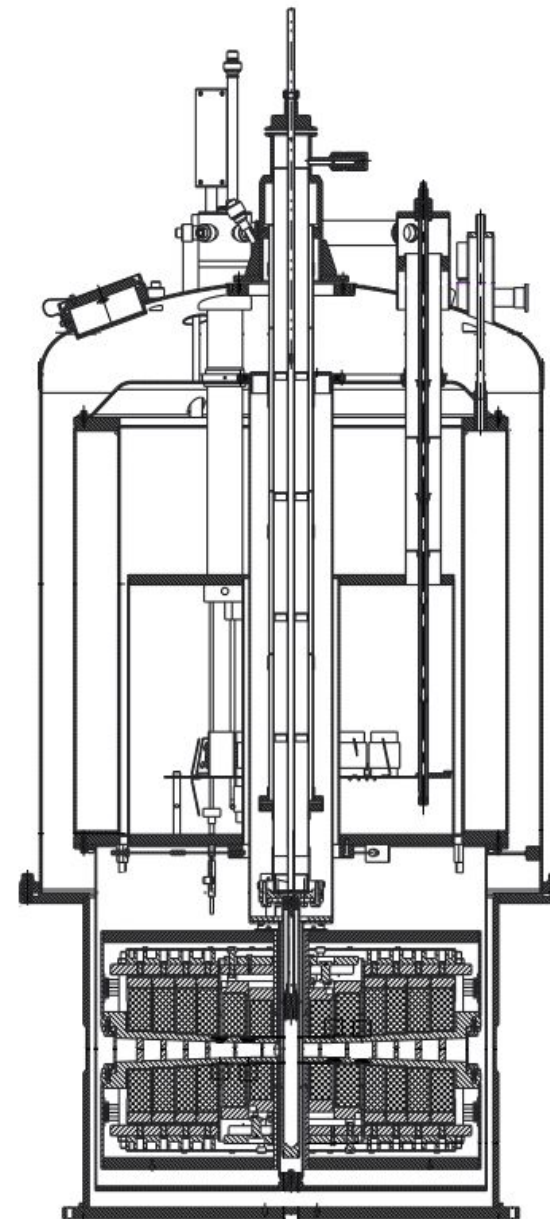
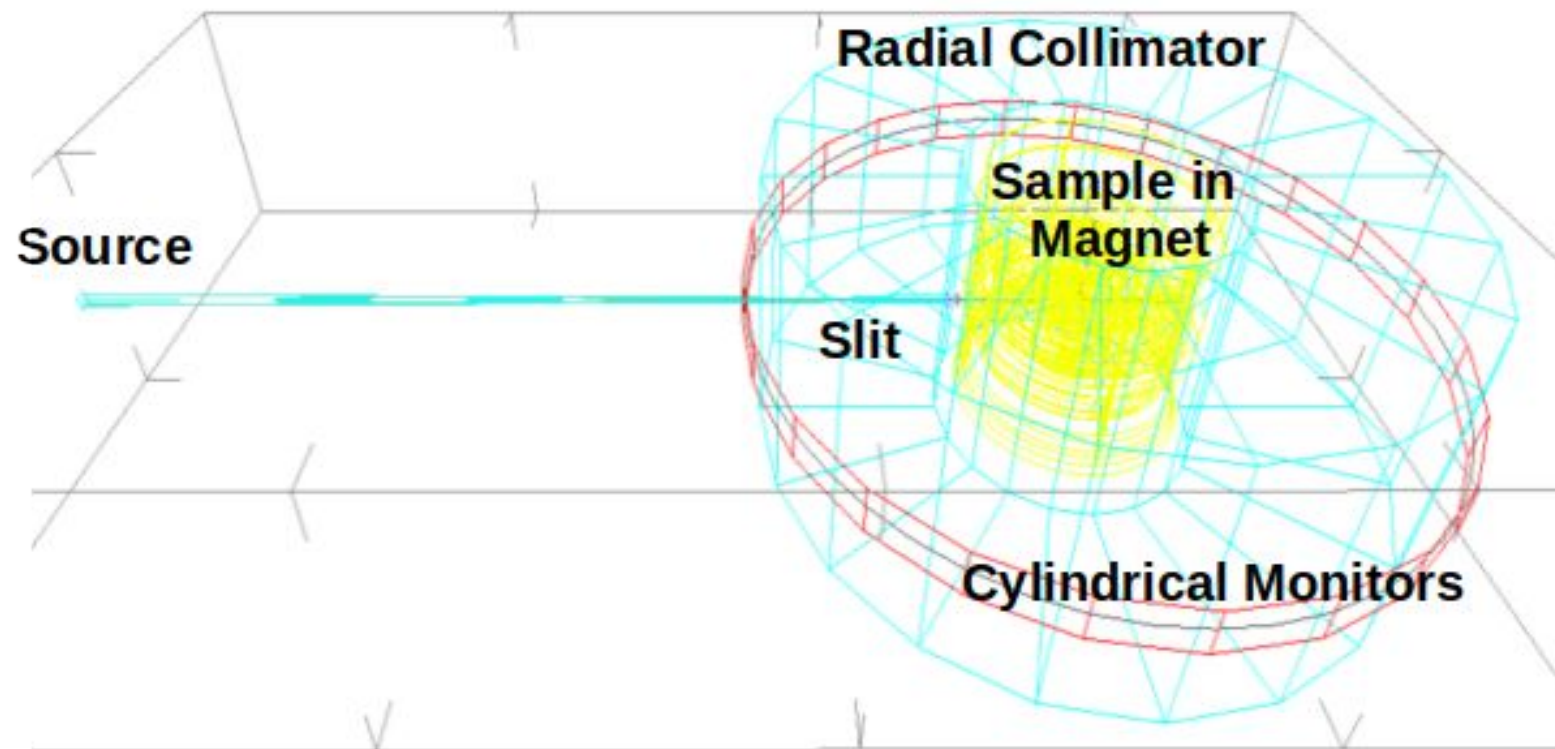
Cryostats

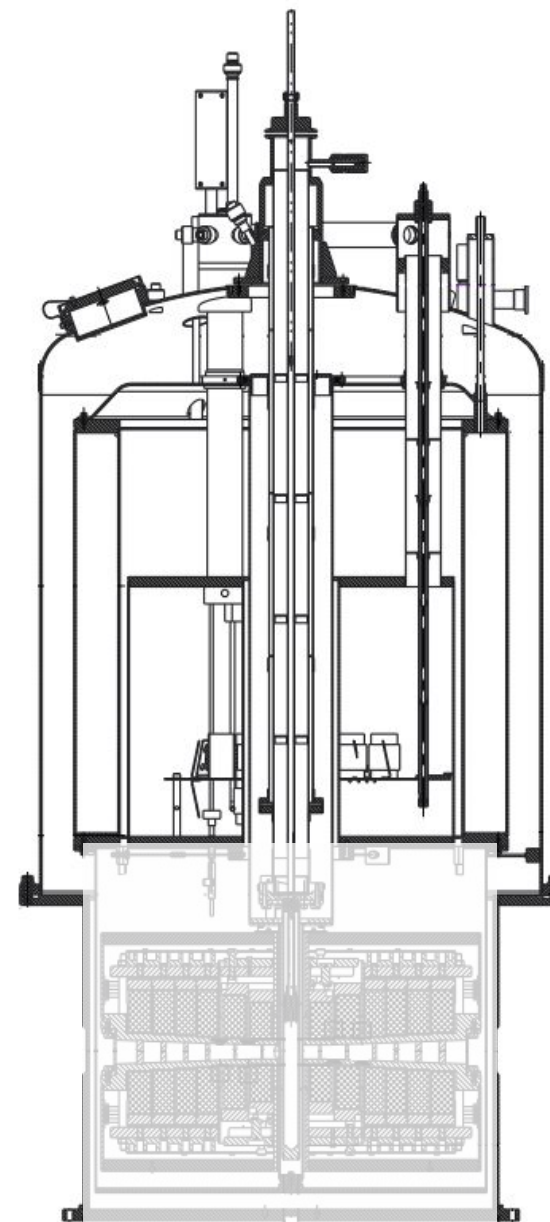
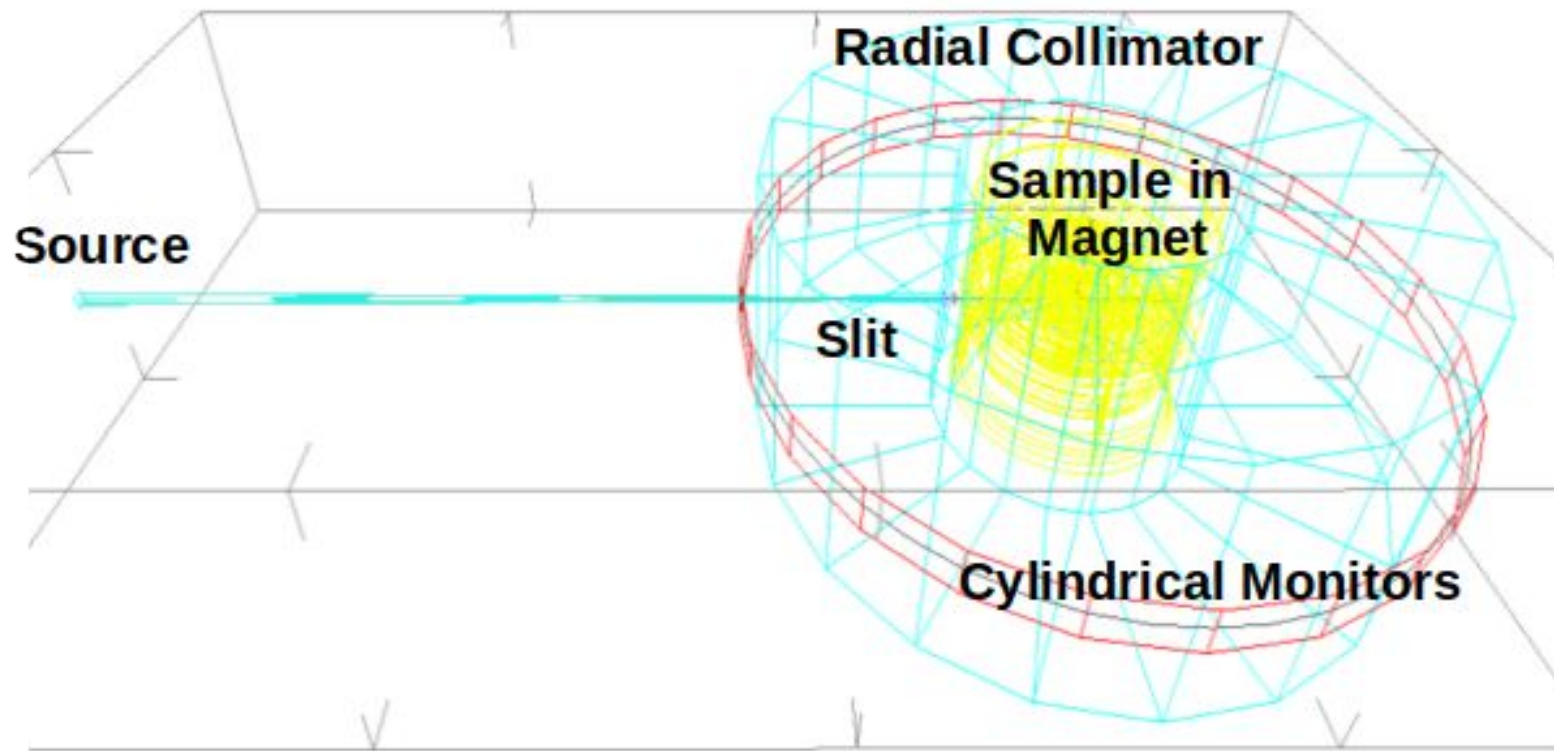
Maintain conditions in the sample environment



Simulating the Sample Environment

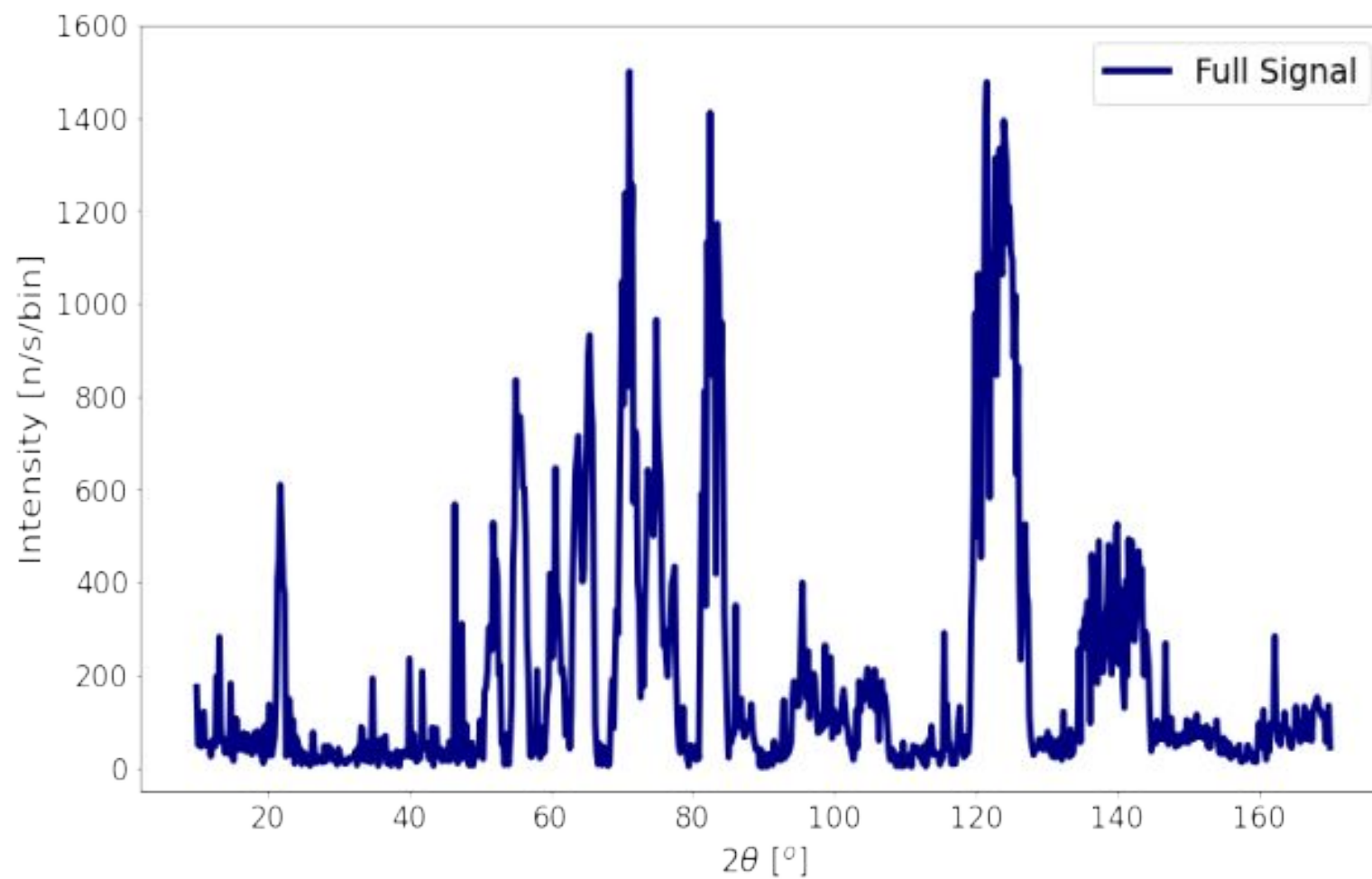




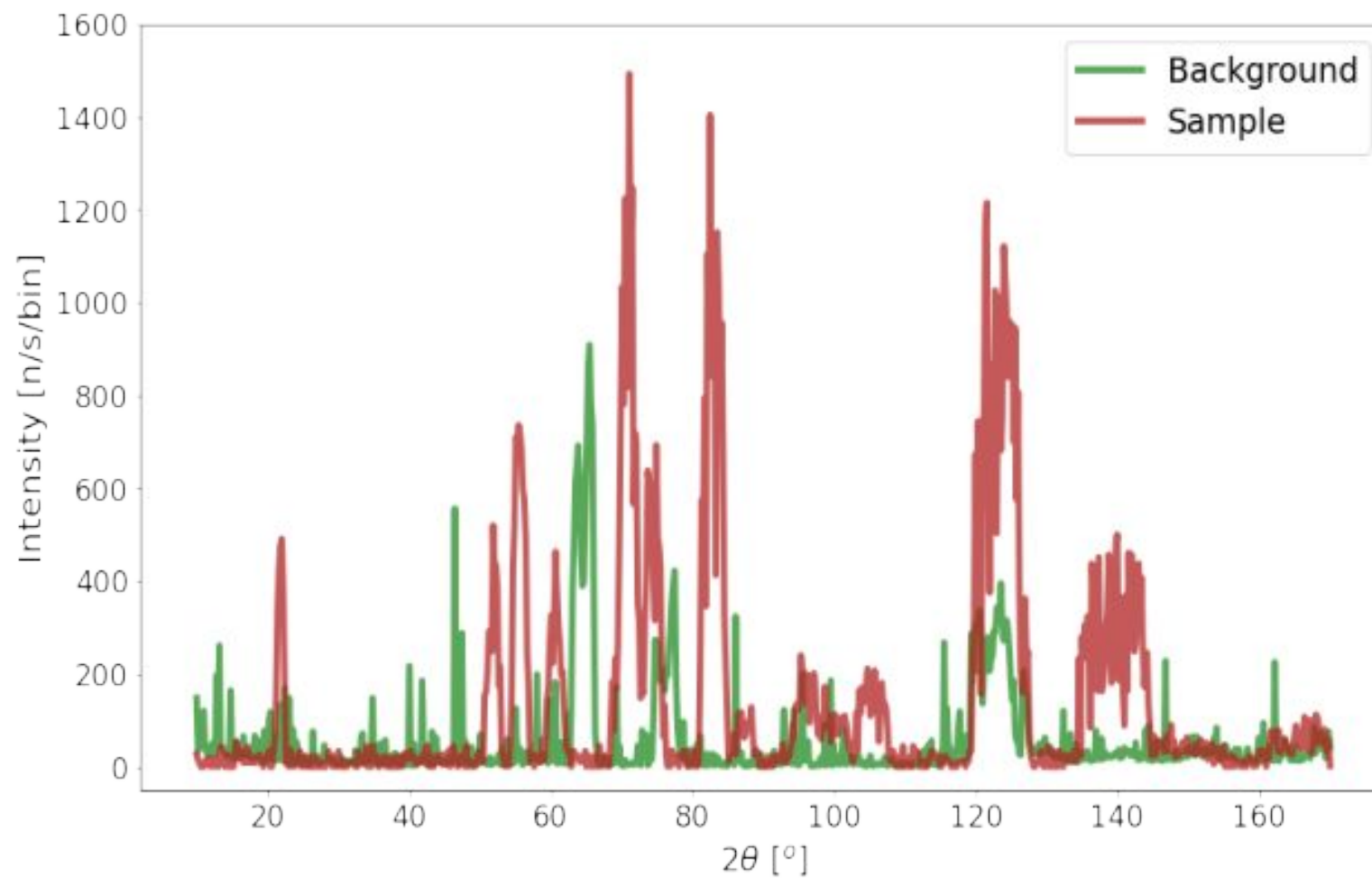


What problem do we need to solve?

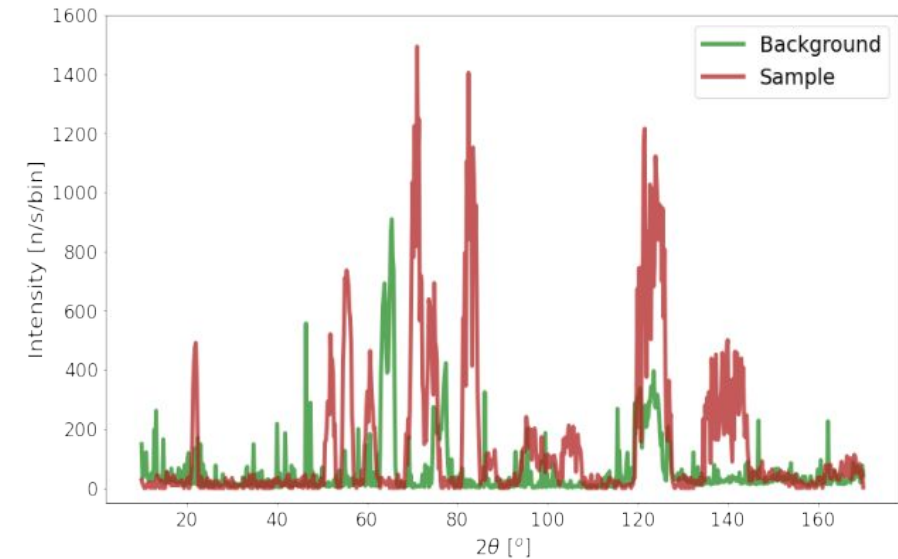
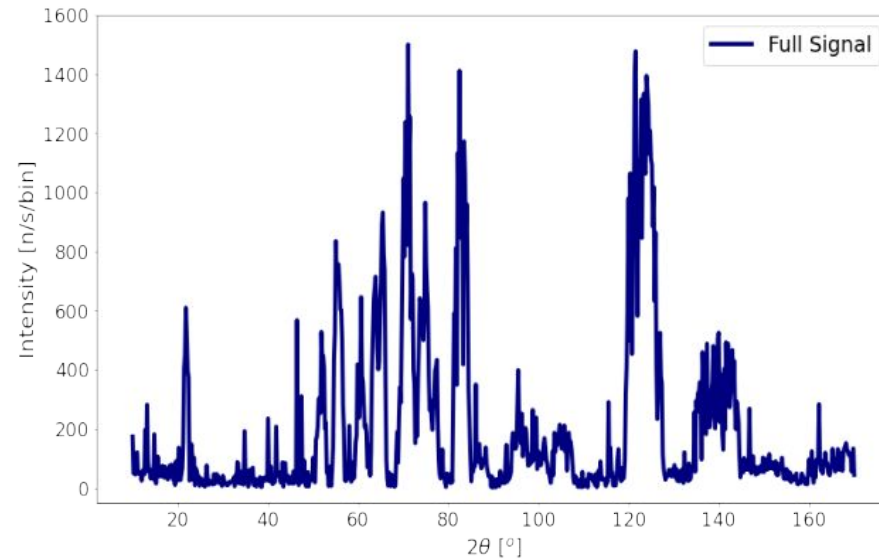
Background Scattering



Background Scattering

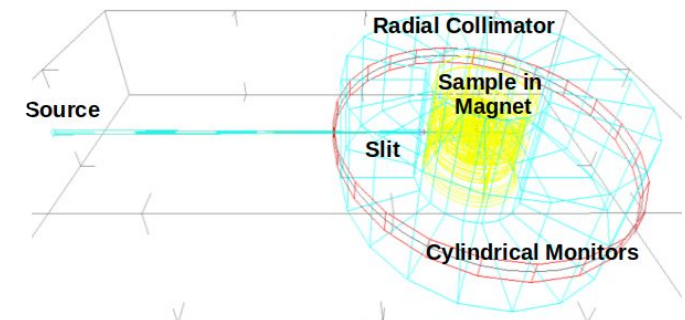


Example: $\text{La}_{2-x}\text{Sr}_x\text{CuO}_4$, $\lambda=1.47 \text{ \AA}$

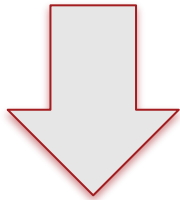
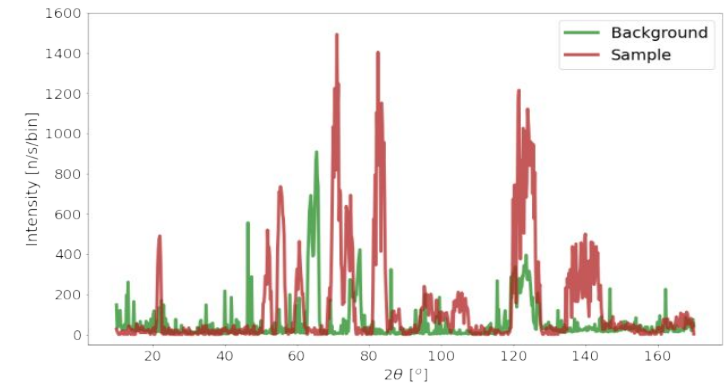
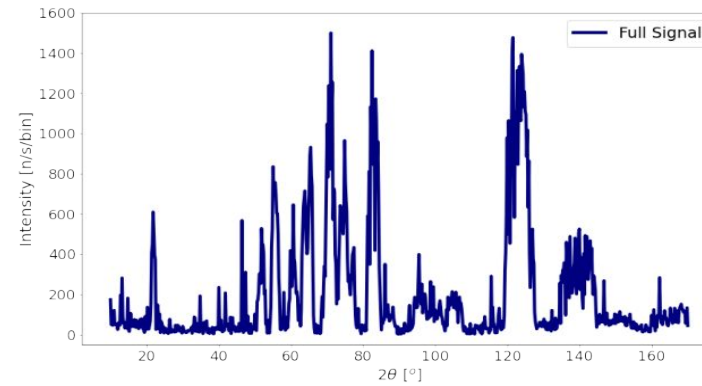


Produced over 24000 sets of synthetic data based on 7 parameters:

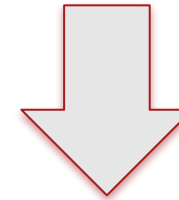
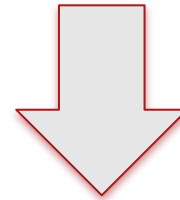
- Wavelength: λ , λ_d
- Beam divergence
- Sample dimension
- Sample - Detector distance
- Sample material



- Wavelength: λ , λ_d
- Beam divergence
- Sample height/radius
- Sample - Detector distance
- Sample material

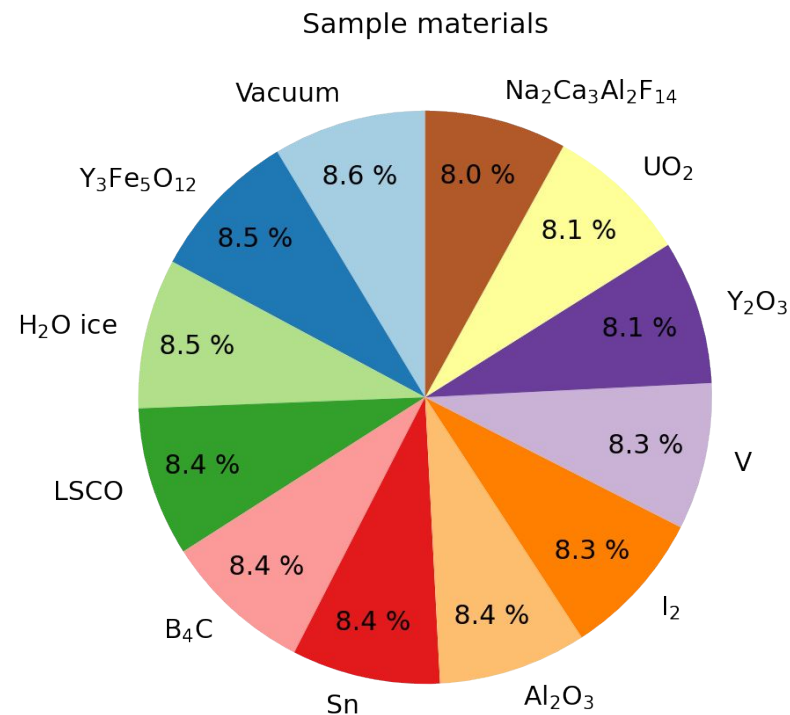
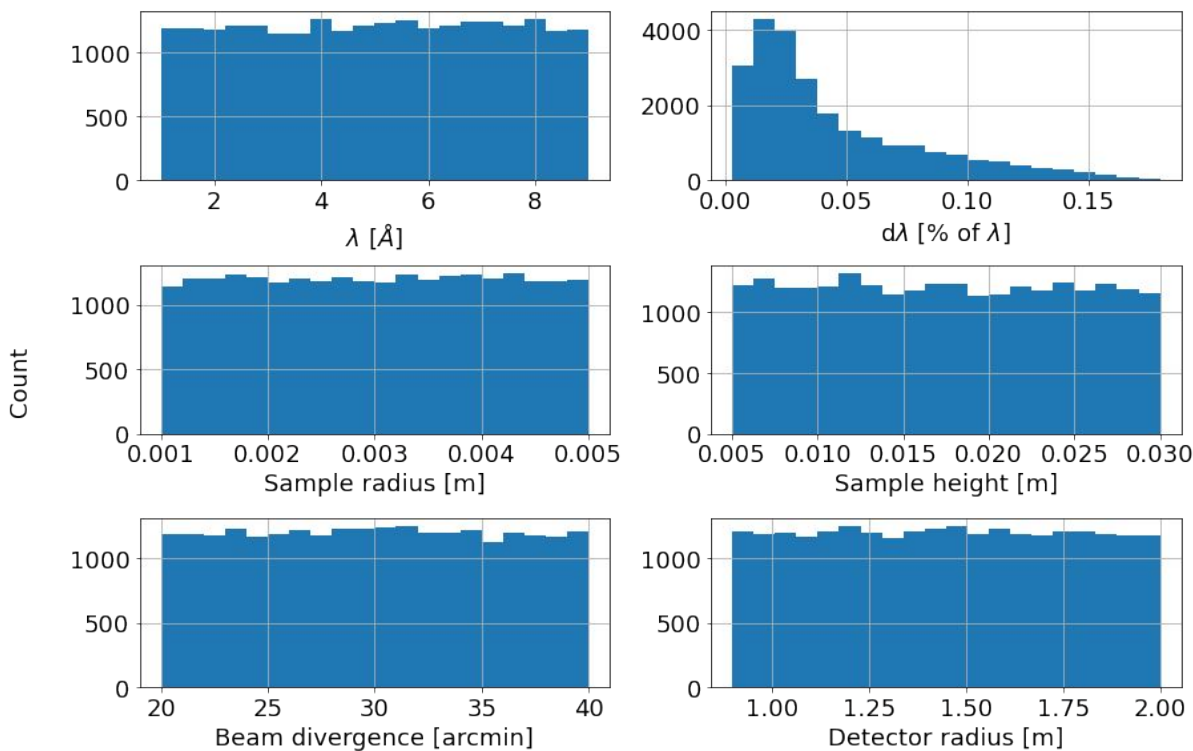
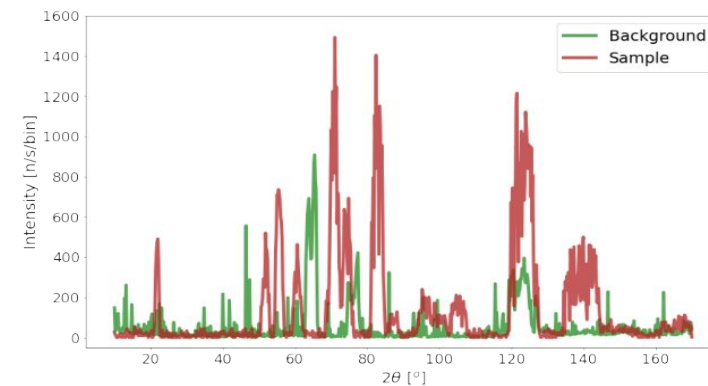
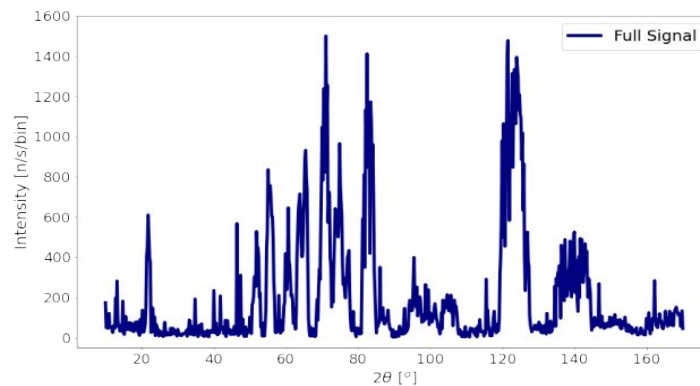


Features



Target Values

- Wavelength: λ , λ_d
- Beam divergence
- Sample height/radius
- Sample - Detector distance
- Sample material

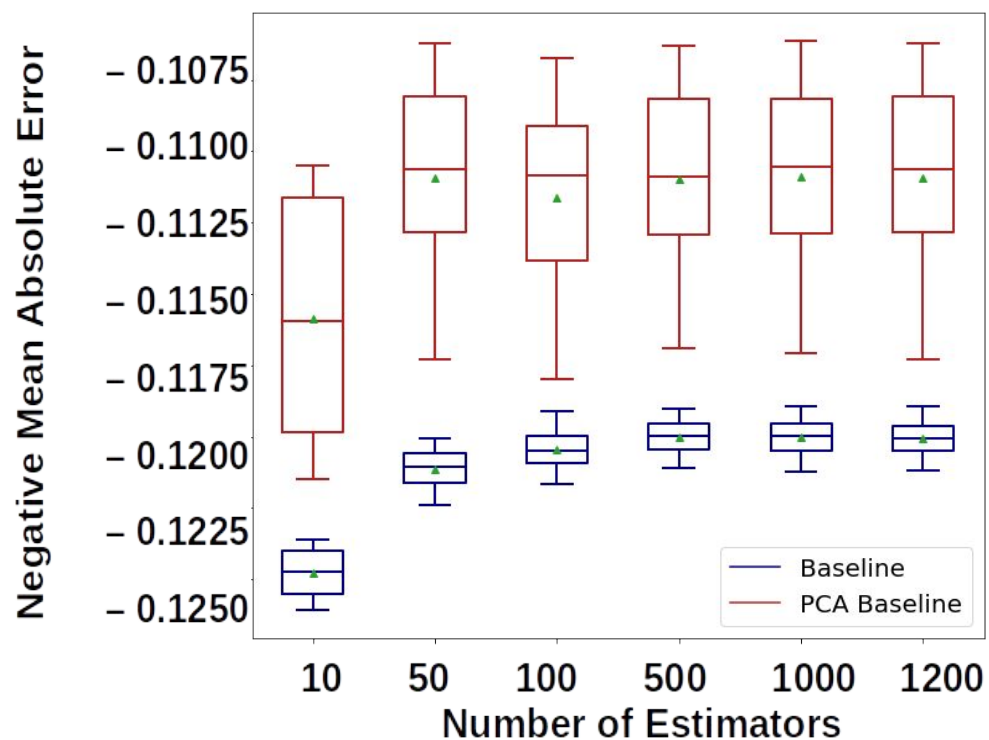


What's the best way to predict background?

Starting with a Random Forest:

1. Features: High dimensional or reduced?
2. Information - Complexity trade-off
3. Background information - bias exploration

1. Dimensionality Reduction



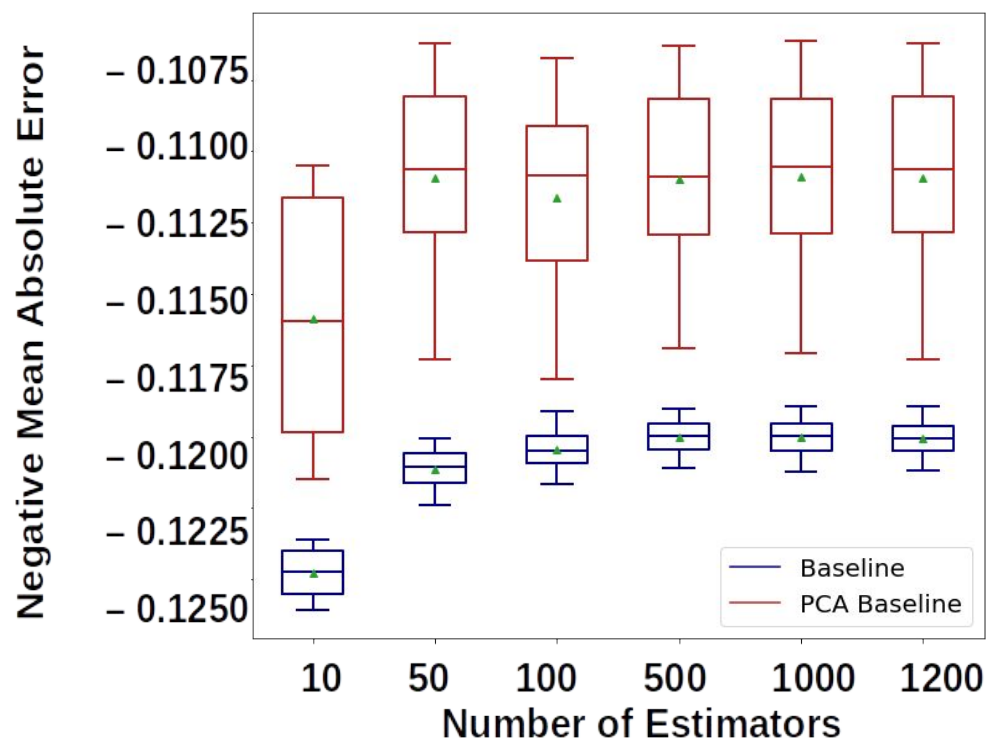
High dimensionality: 807 features

- 7 Instrument parameters
- 800 intensity/angle values

PCA: 81 features

- 89.96% of feature reduction
- 94.45% of information preserved

1. Dimensionality Reduction



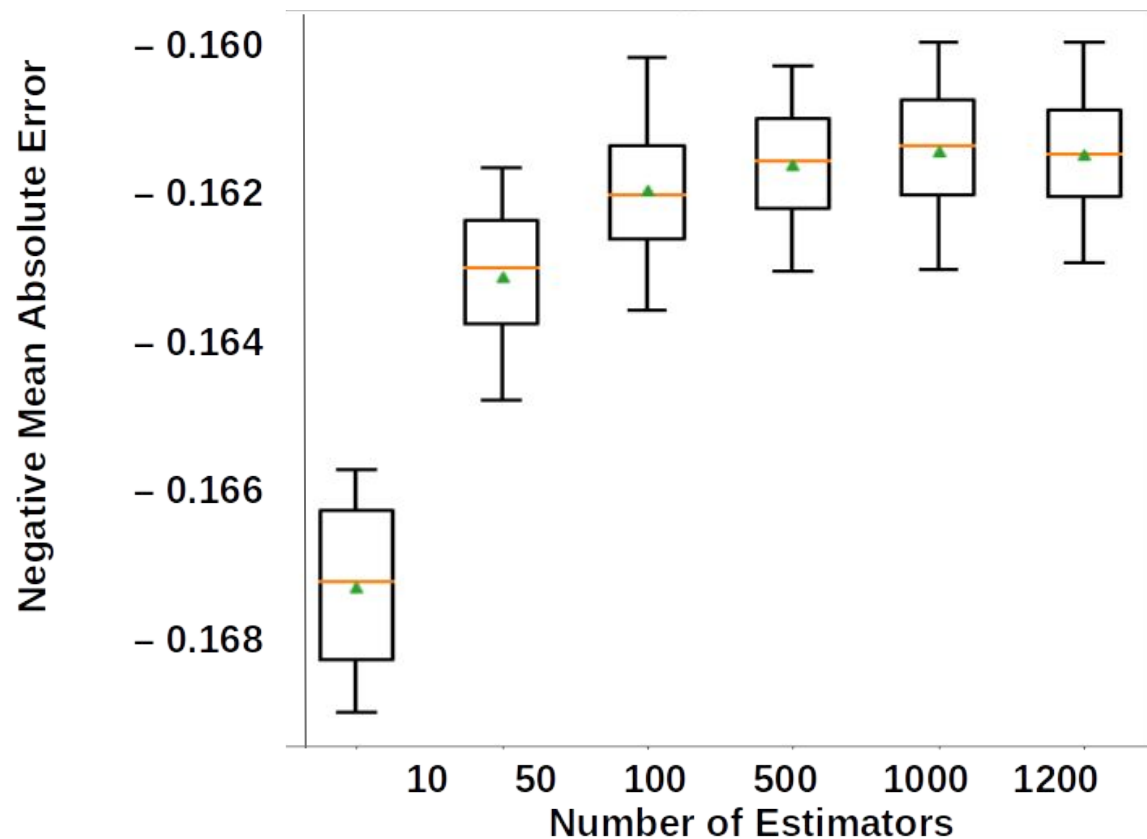
High dimensionality: 807 features

- 7 Instrument parameters
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PCA: 81 features

- **89.96% of feature reduction**
- **94.45% of information preserved**

2. Information vs Complexity in target values

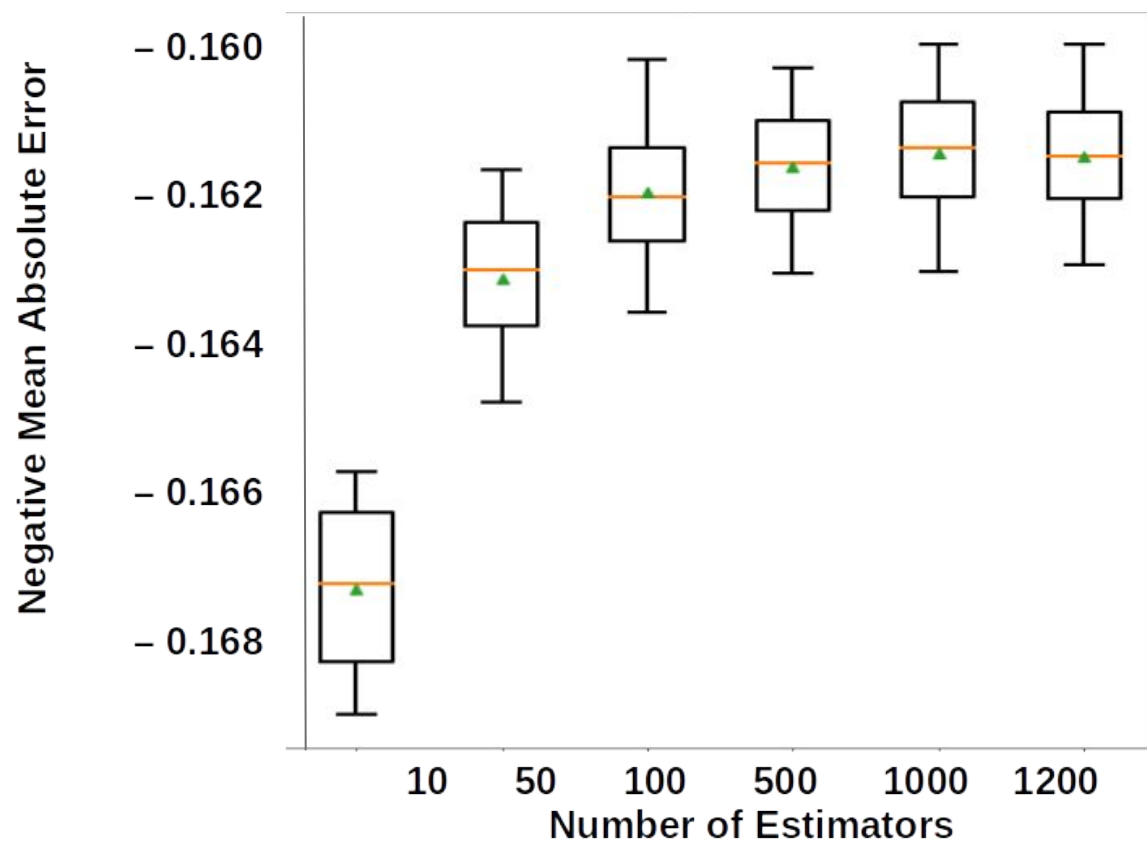


5 bins per degree: 800 targets
MAE: 0.161

1 bin per degree: 160 targets
MAE: 0.111

Normalised Intensity within $10^\circ - 170^\circ$

2. Information vs Complexity in target values

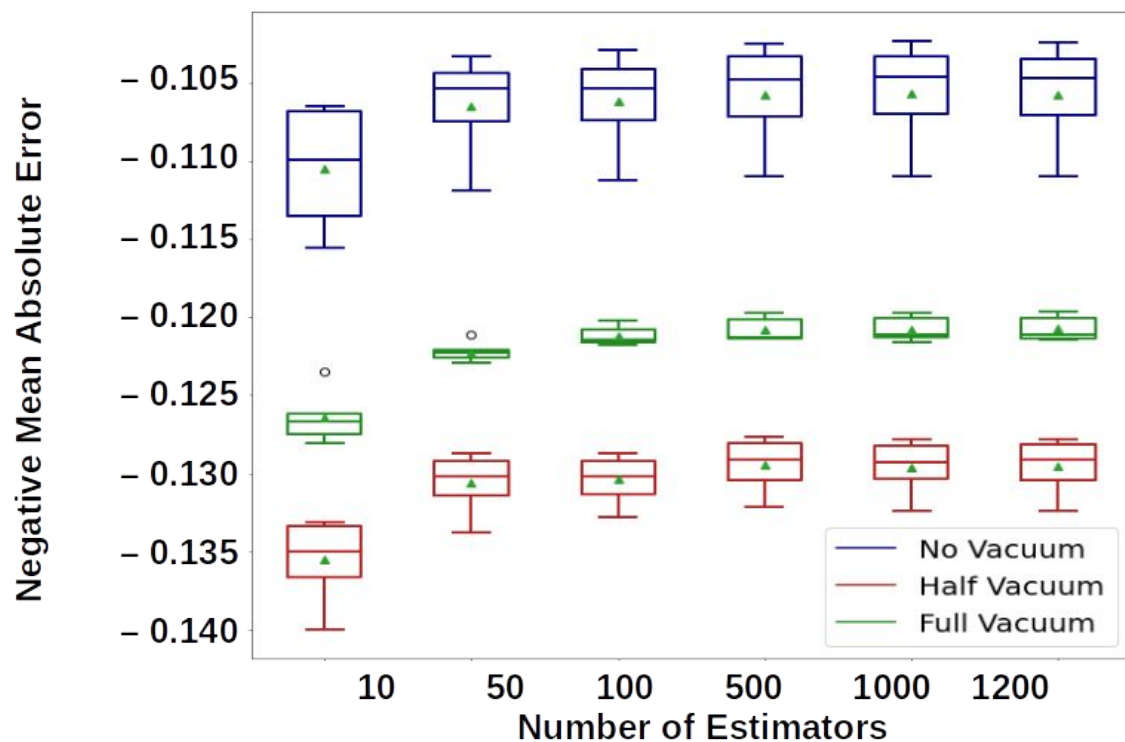


Normalised Intensity within 10° - 170°

5 bins per degree: 800 targets
MAE: 0.161

1 bin per degree: 160 targets
MAE: 0.111

3. Bias Exploration: Measurements of *pure background*

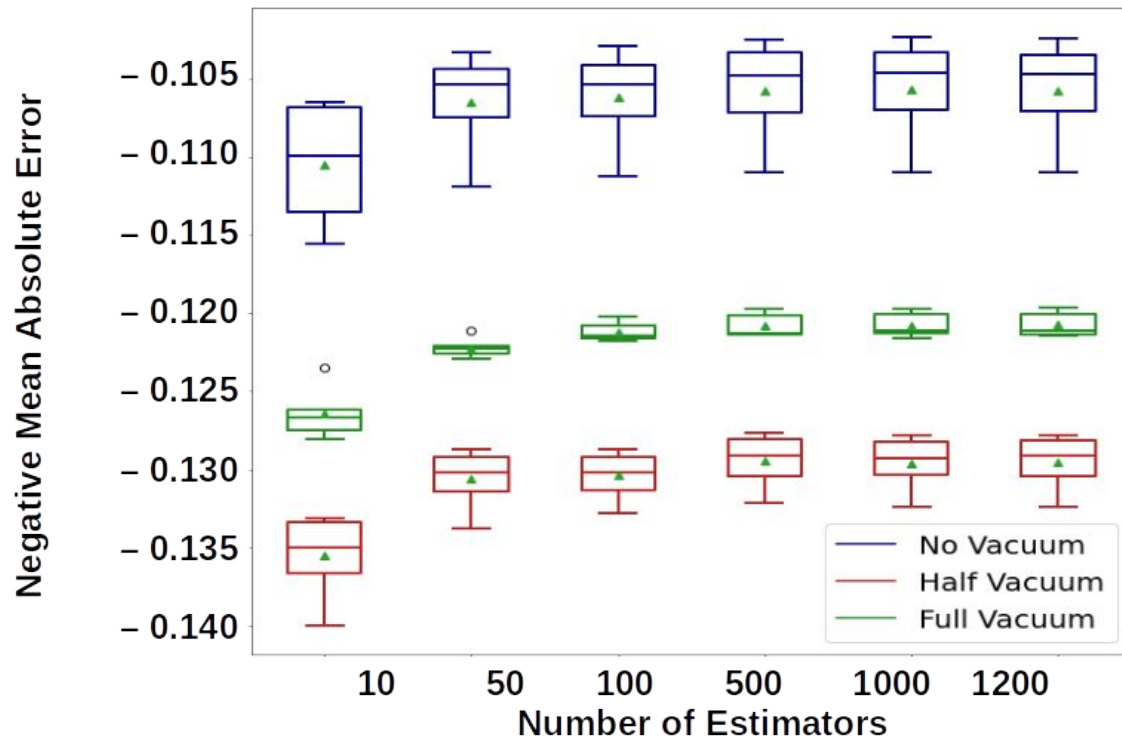


0% Background Measurements
MAE: 0.105

50% Background Measurements
MAE: 0.129

100% Background Measurements
MAE: 0.121

3. Bias Exploration: Measurements of *pure background*

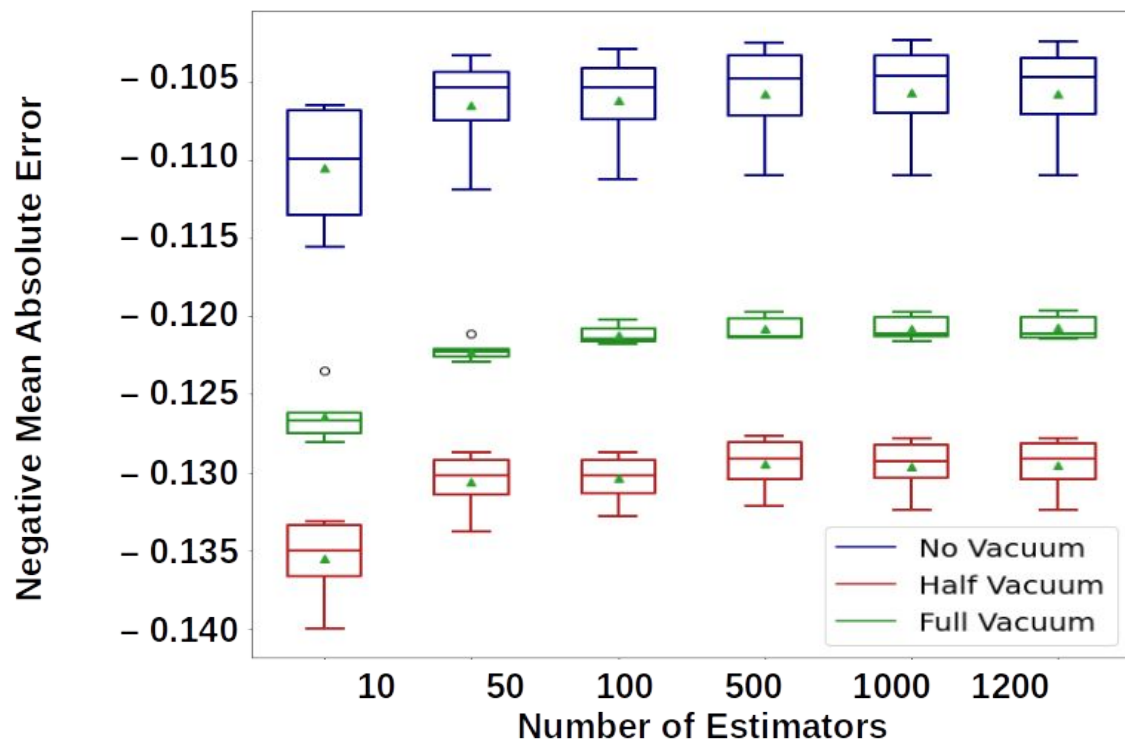


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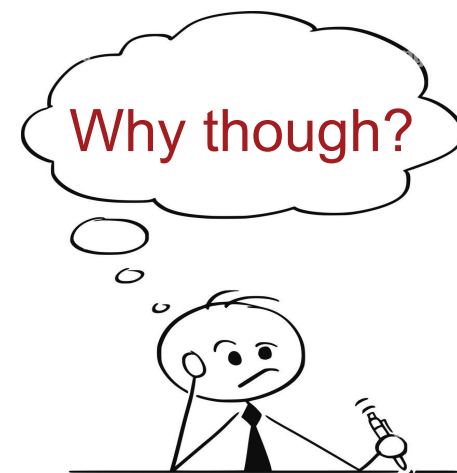
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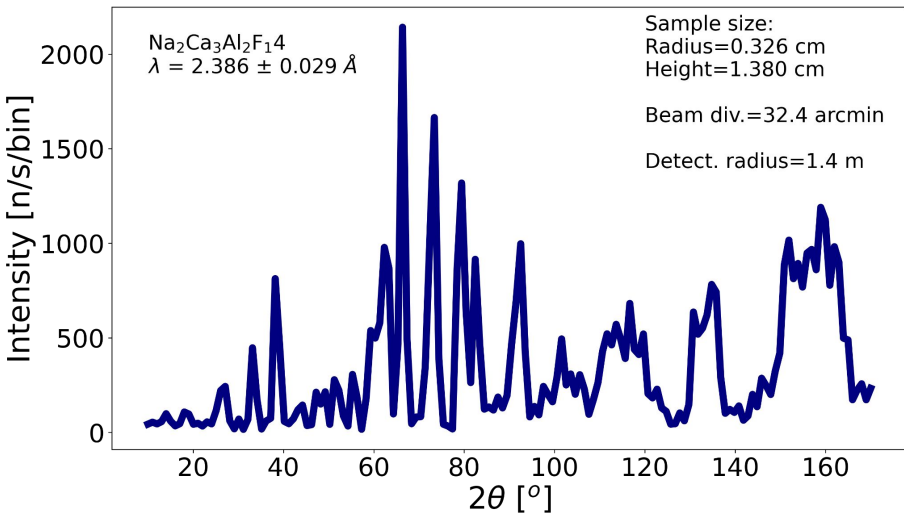
100% Background Measurements
MAE: 0.121



First results

Random Forest vs Gradient Boost

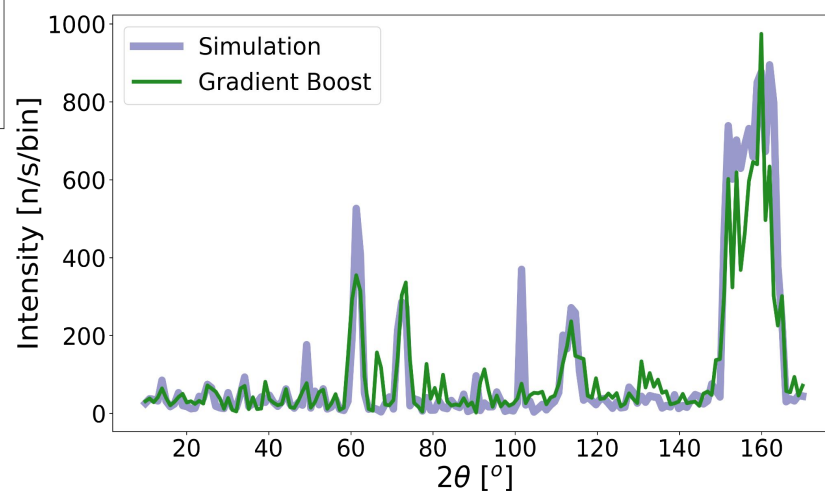
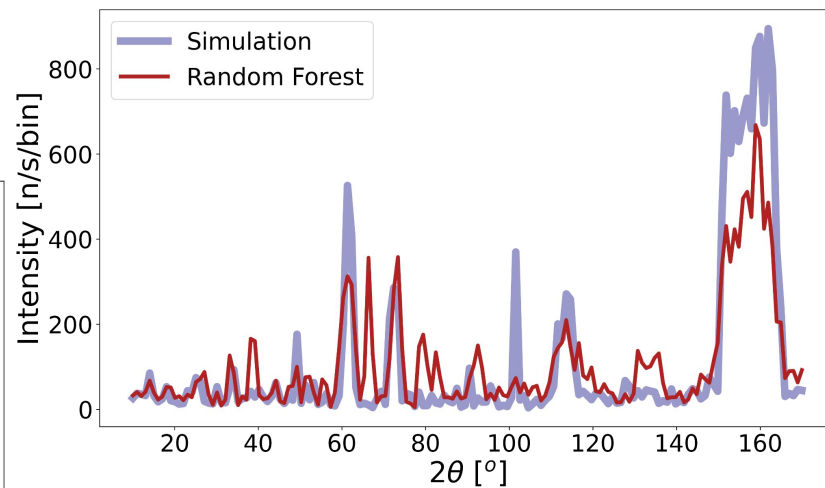
Simulation



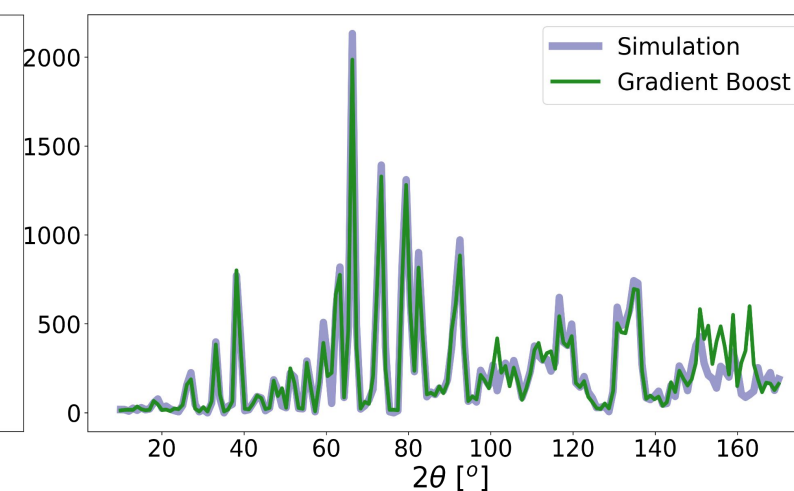
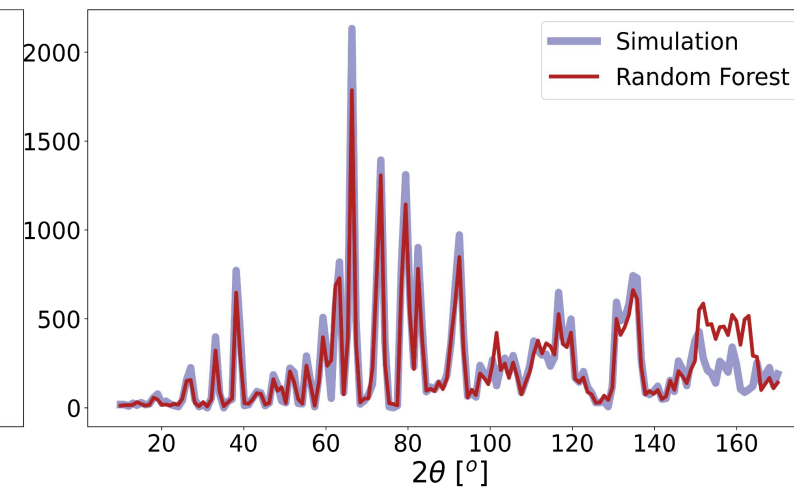
Overall Performance

Model	Random Forest	Gradient Boost
MAE	0.1215	0.1192

Predicted Background



Predicted Sample



Still a work in progress...

- Improve data: Simulation quality and better representation of materials
- Restructuring the database under the F.A.I.R. framework
- Try Neural Networks - open to suggestions
- Generalise: Material-agnostic model
- Synthetic + Real data hybrid

Nonetheless...

First step in background prediction in neutron scattering data

Thank you!

Questions?

