ARUP Imperial College London

Bayesian Machine Learning for Quantifying Uncertainty in Surrogate Modelling

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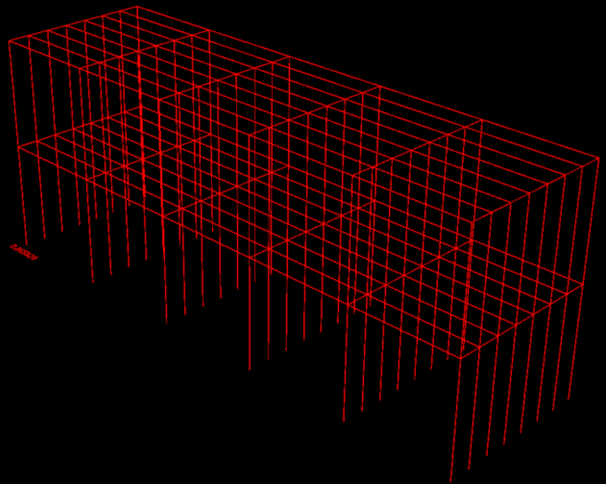
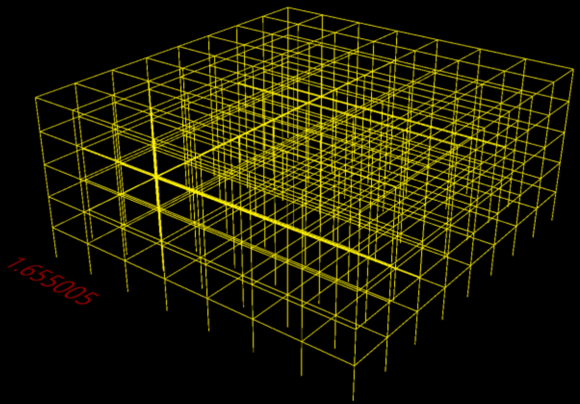
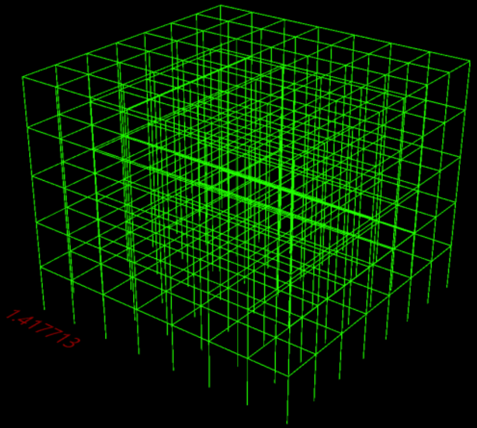
09:00, 14th September 2022







Background | Project Objective

Develop uncertainty-aware Neural Network-based surrogate models that can predict the modal frequencies of 3D structures and communicate the uncertainty in those predictions.

Background | Modal Analysis

- → Modal analysis predicts the resonant frequencies of structures
- → Modal frequencies of a structure shouldn't match frequency of:
  - → Earthquakes
  - → Footsteps and sway
  - → Wind flutter

Mexico City earthquake, 1985

Millennium Bridge, London

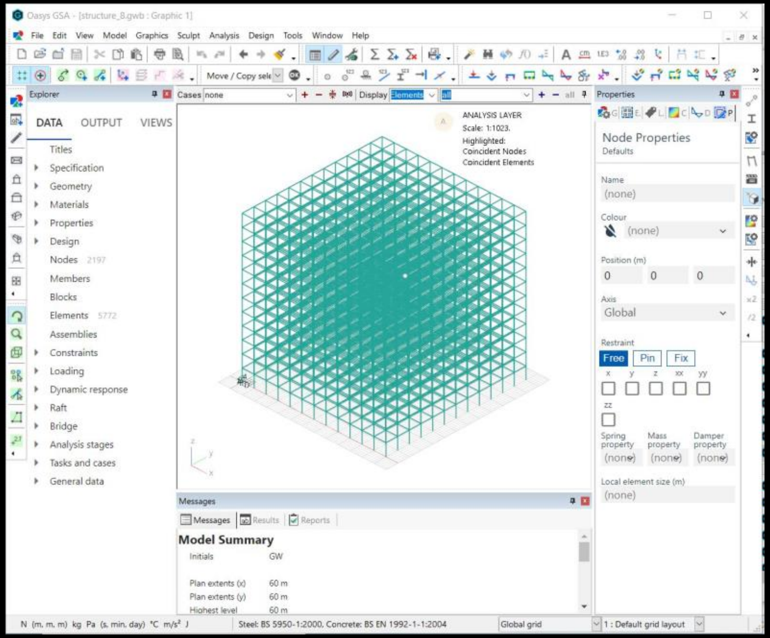
Broughton Bridge collapse, 1826

Background | Modal Analysis Using GSA

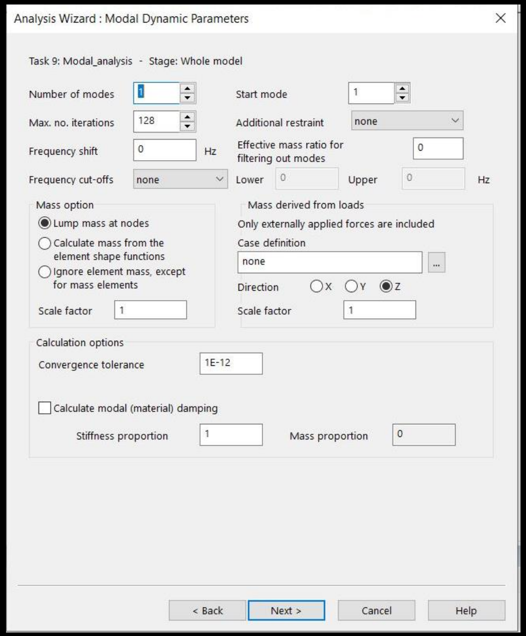
→ Oasys GSA can perform modal analysis

→ Calculates many modal frequencies of a structure

→ Solves a generalised eigenvalue problem



Define geometry



Define simulation parameters

Wait until completion

Background | Advantages / Disadvantages of GSA Analysis

GSA Modal Analysis
Accurate
Explainable
Expensive
Complexity scales with size of structure
Platform-specific
Automation requires APIs/SDKs
Specific to one problem

Background | Surrogate Models

What?

→ Lightweight models approximating physical systems/simulations

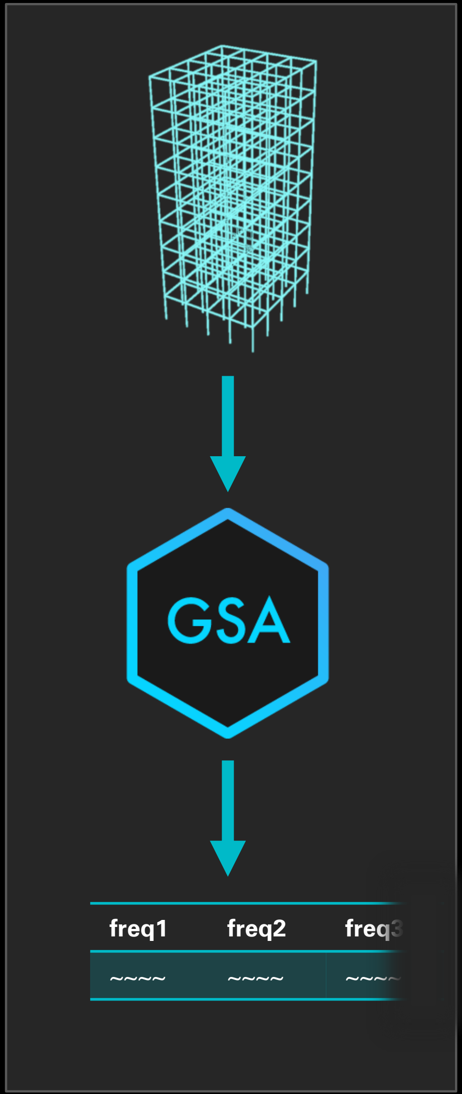
Why?

→ Rapid prototyping

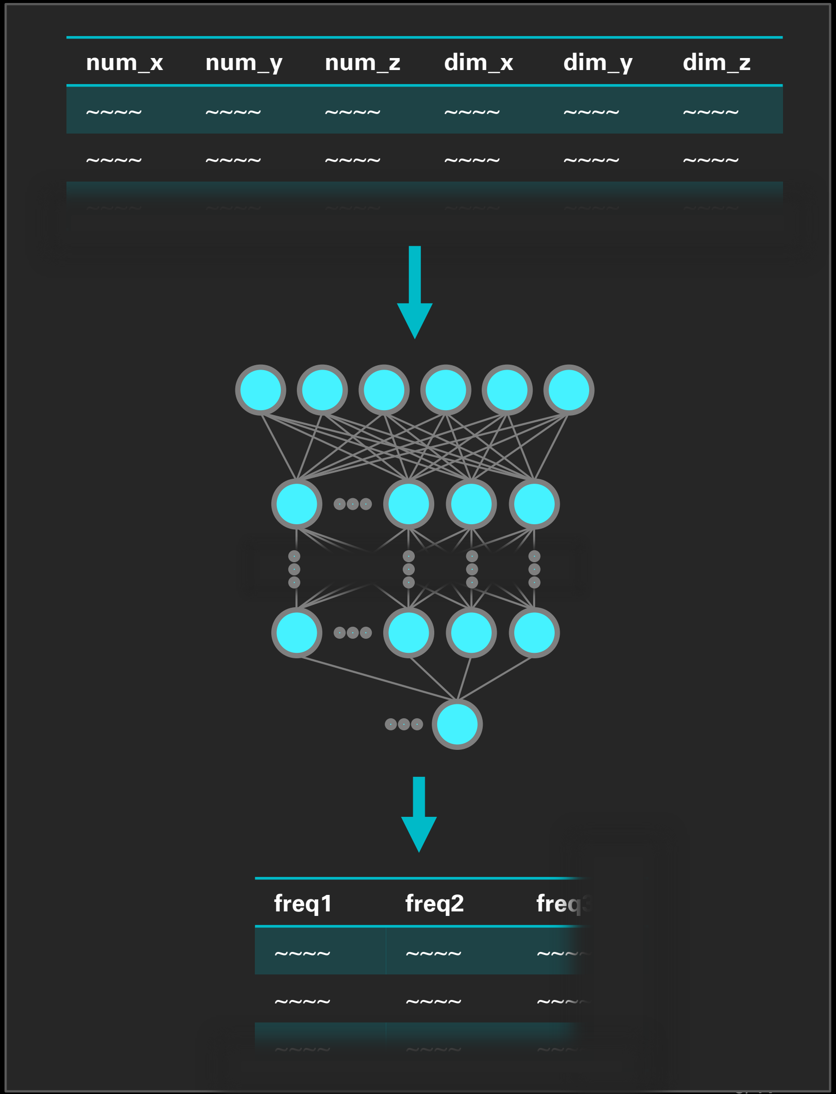
→ Inverse problems

How?

→ Neural network trained on data generated from simulations/observations



Base simulation



NN-based surrogate

Background | Surrogate vs GSA Analysis

GSA Modal Analysis	**Modal Analysis via NN-based surrogate**
Accurate	Is an approximation
Explainable	Challenging to explain
Expensive	Cheap predictions
Complexity scales with size of structure	Complexity constant w.r.t. size of structure
Platform-specific	Platform agnostic / portable
Automation requires APIs/SDKs	Automation very straightforward
Specific to one problem	Applicable to many problems

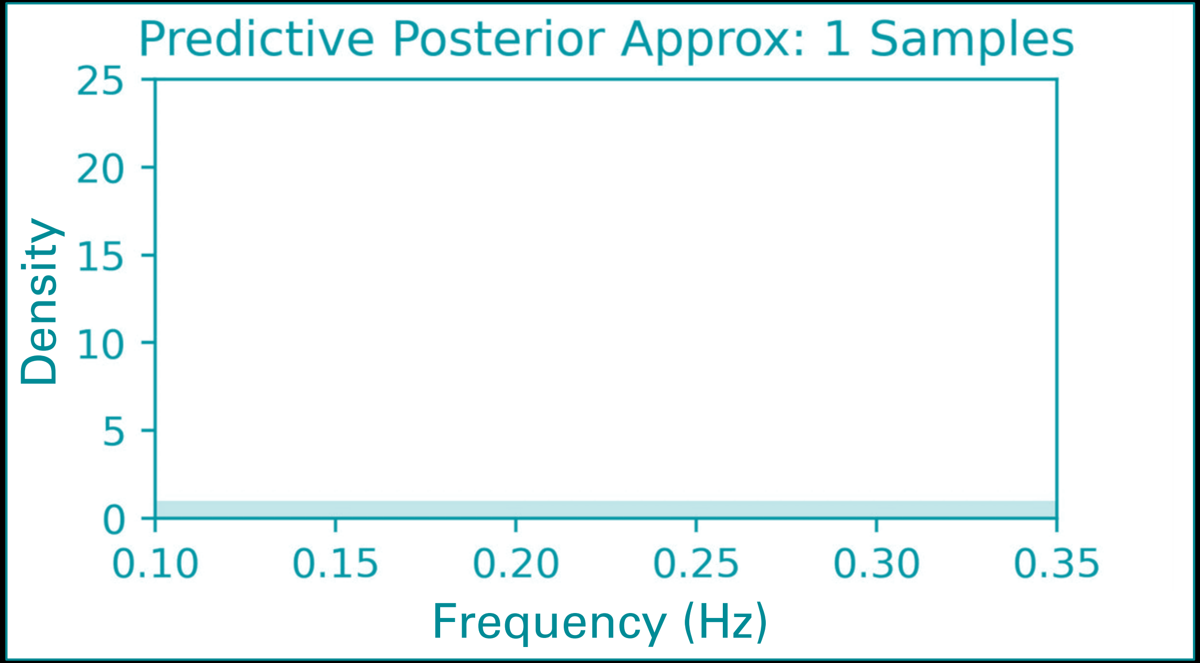
Methodology | Bayesian Neural Networks (BNNs)

→ Two Bayesian Neural Network (BNN) methods investigated:

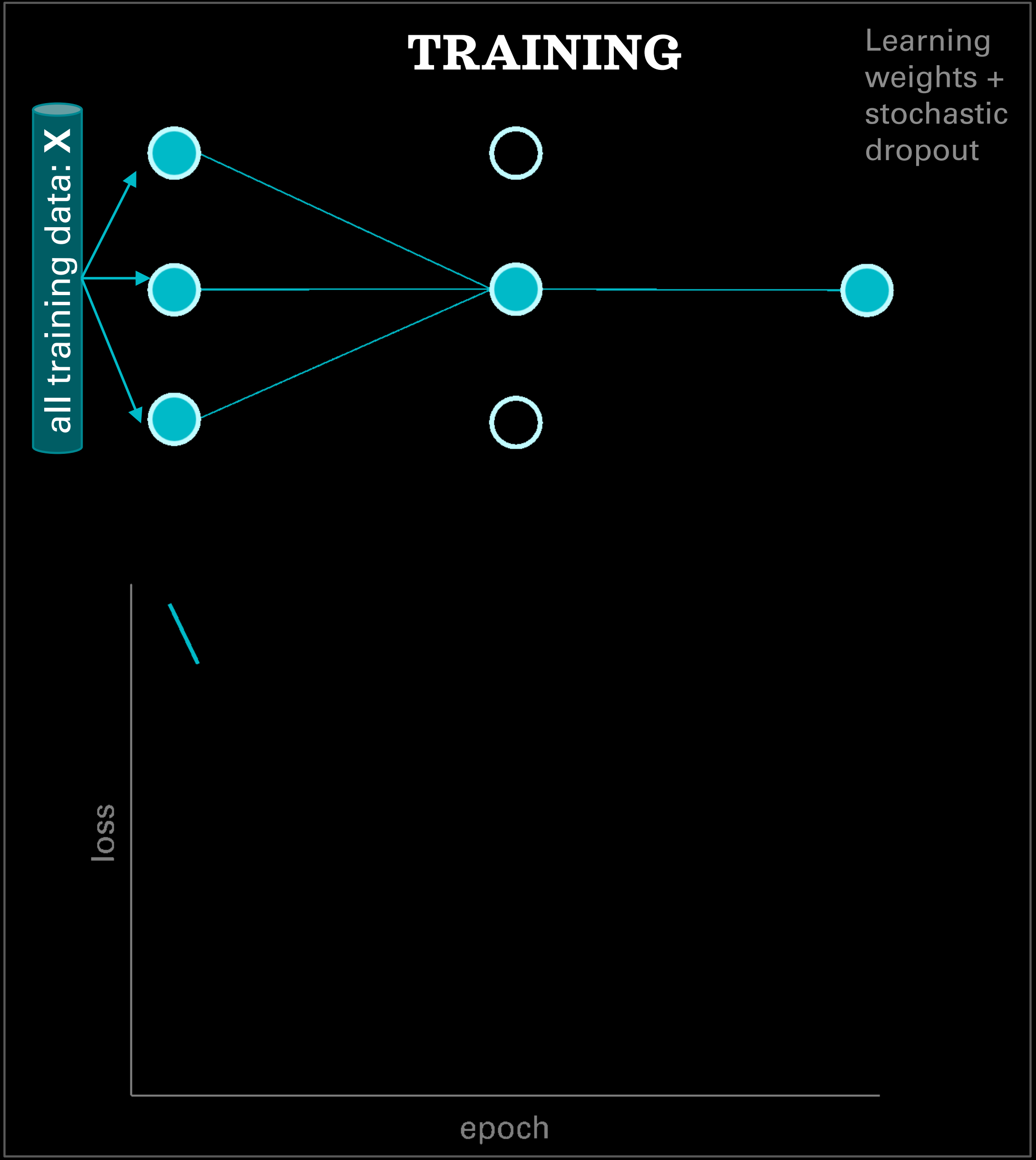
1. MC Dropout *(Gal and Ghahramani, 2016)*
2. Stochastic Gradient Langevin Dynamics (SGLD) *(Welling et al., 2011)*

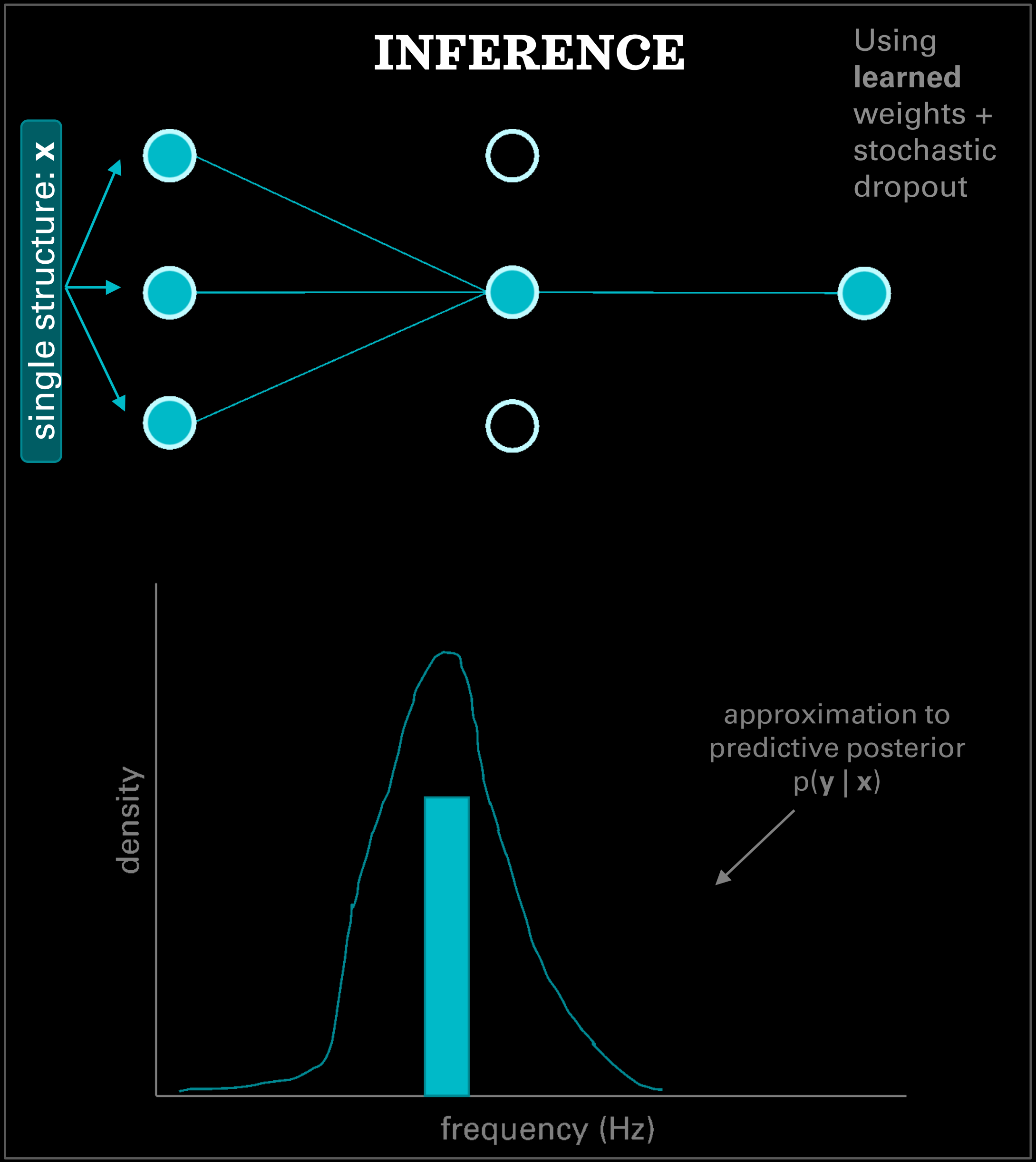
→ Both methods apply stochasticity.

Sampling stochastic outputs => approximation to predictive posterior distribution

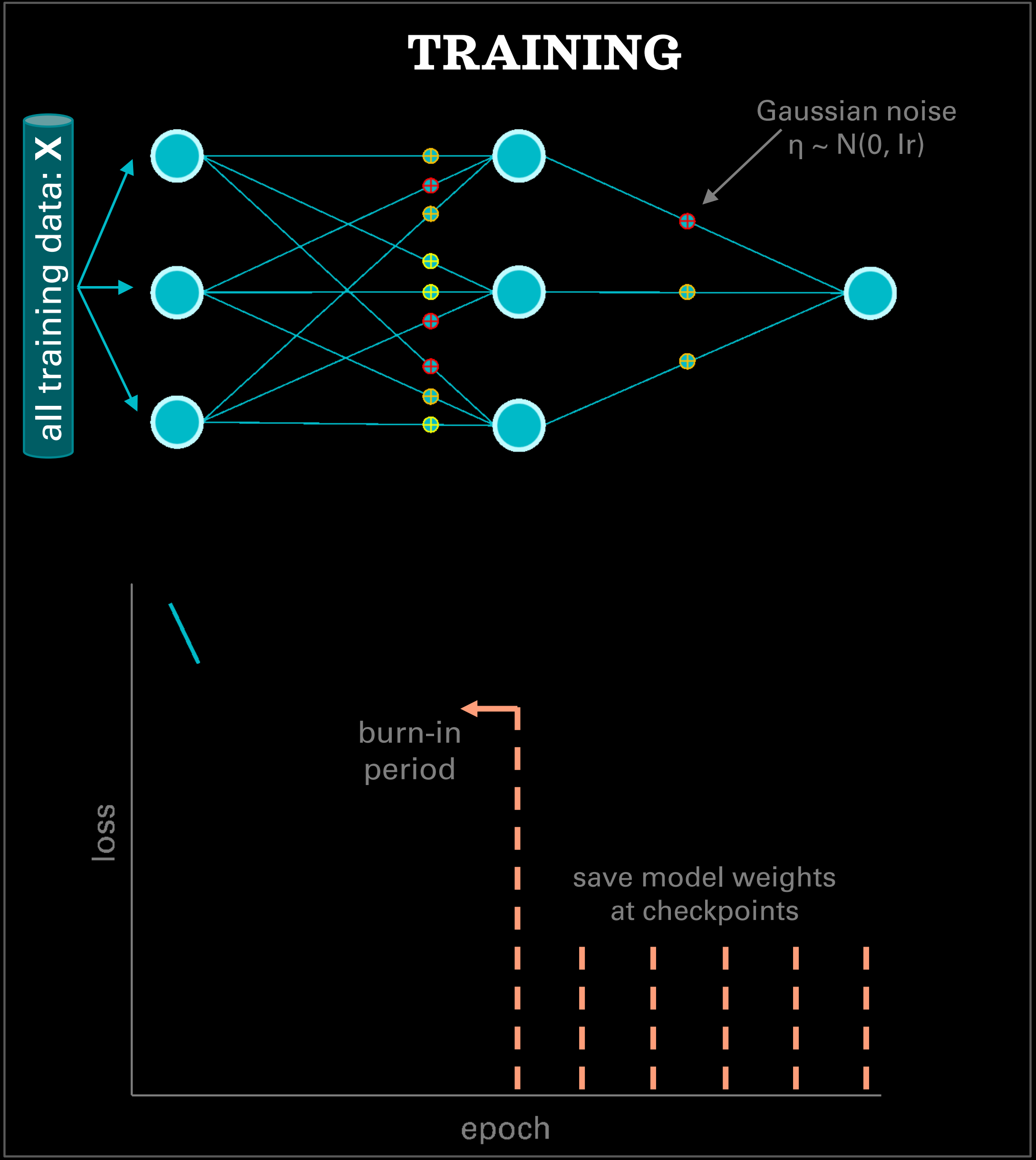


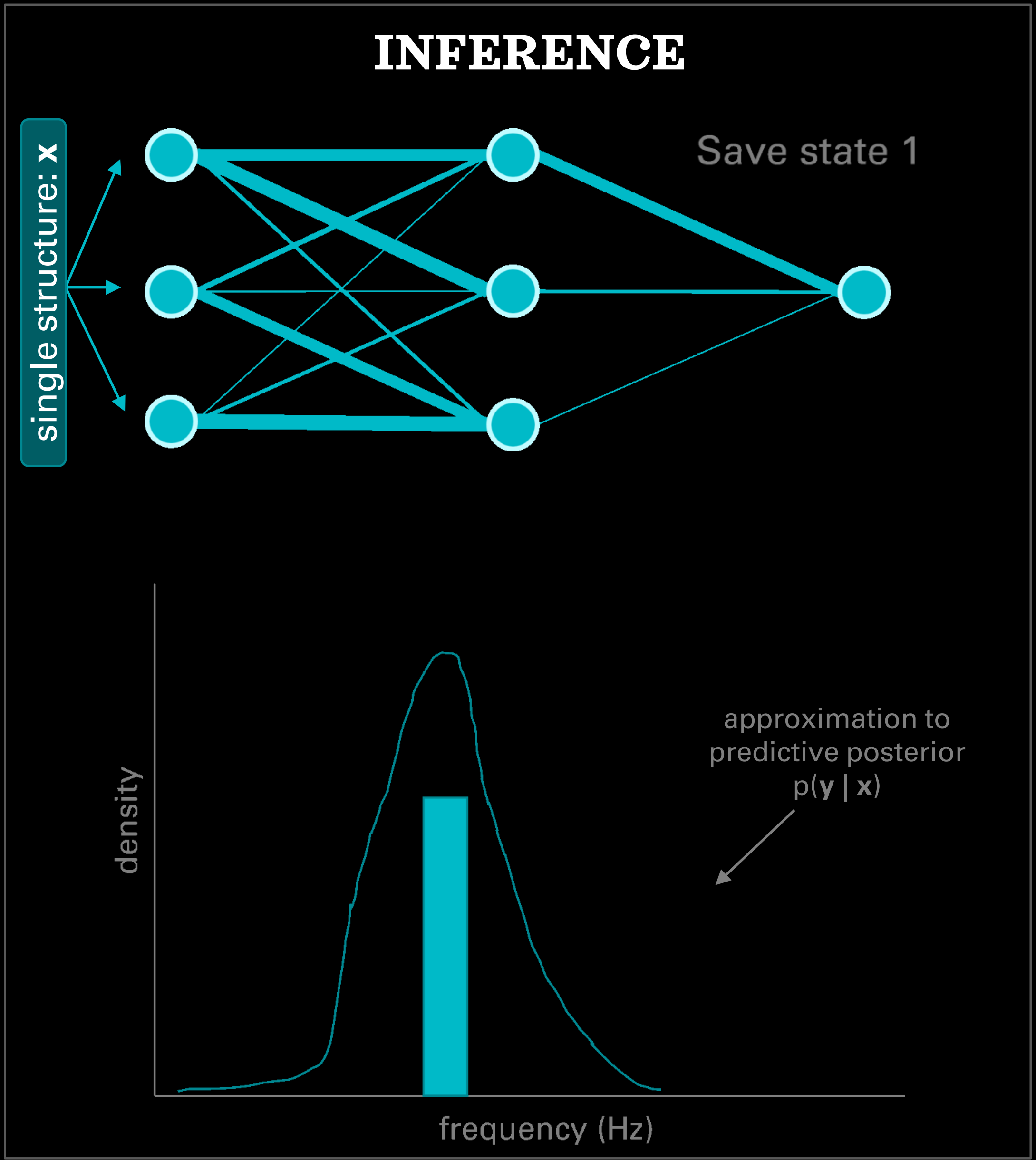
Methodology | MC Dropout



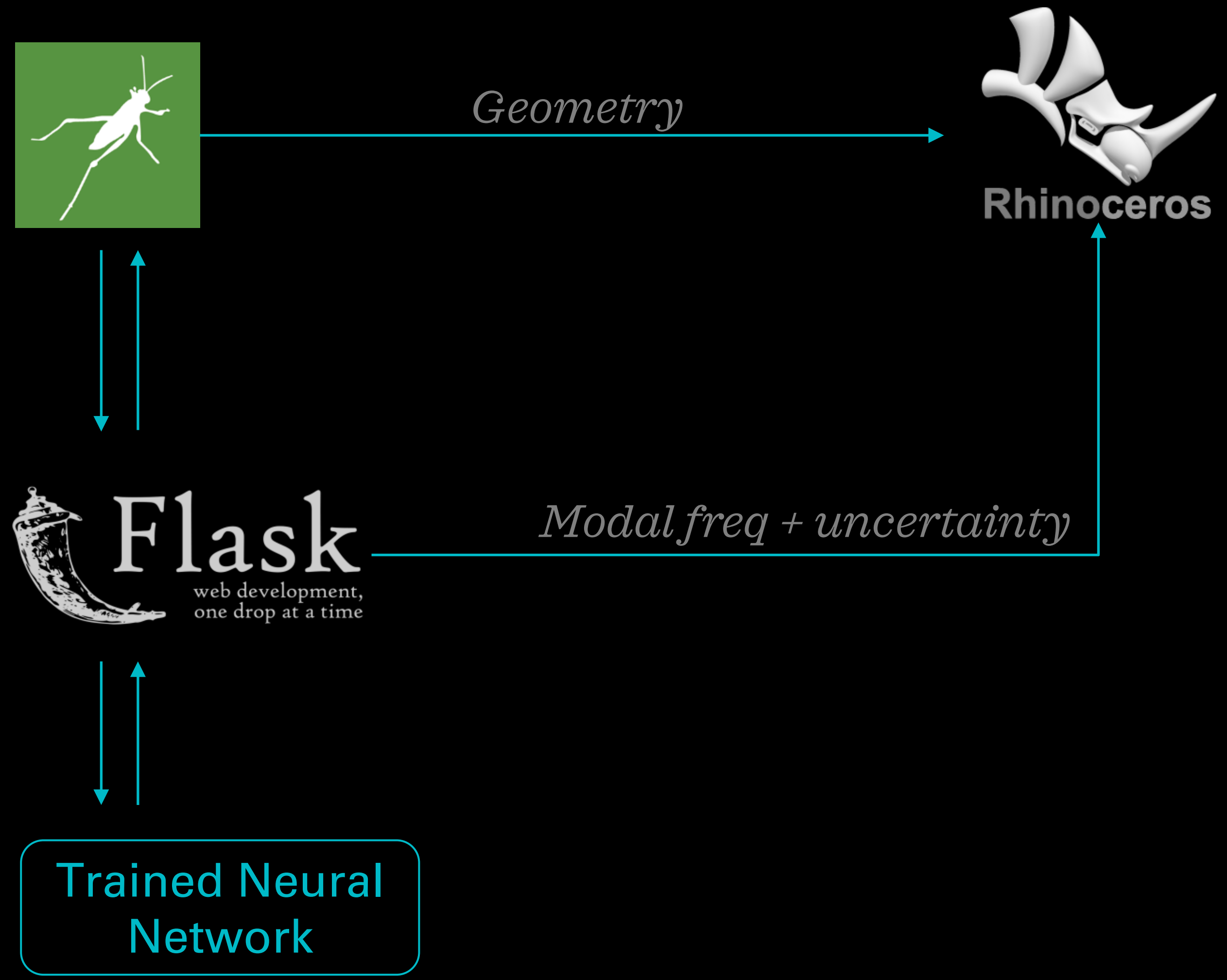


Methodology | Stochastic Gradient Langevin Dynamics (SGLD)

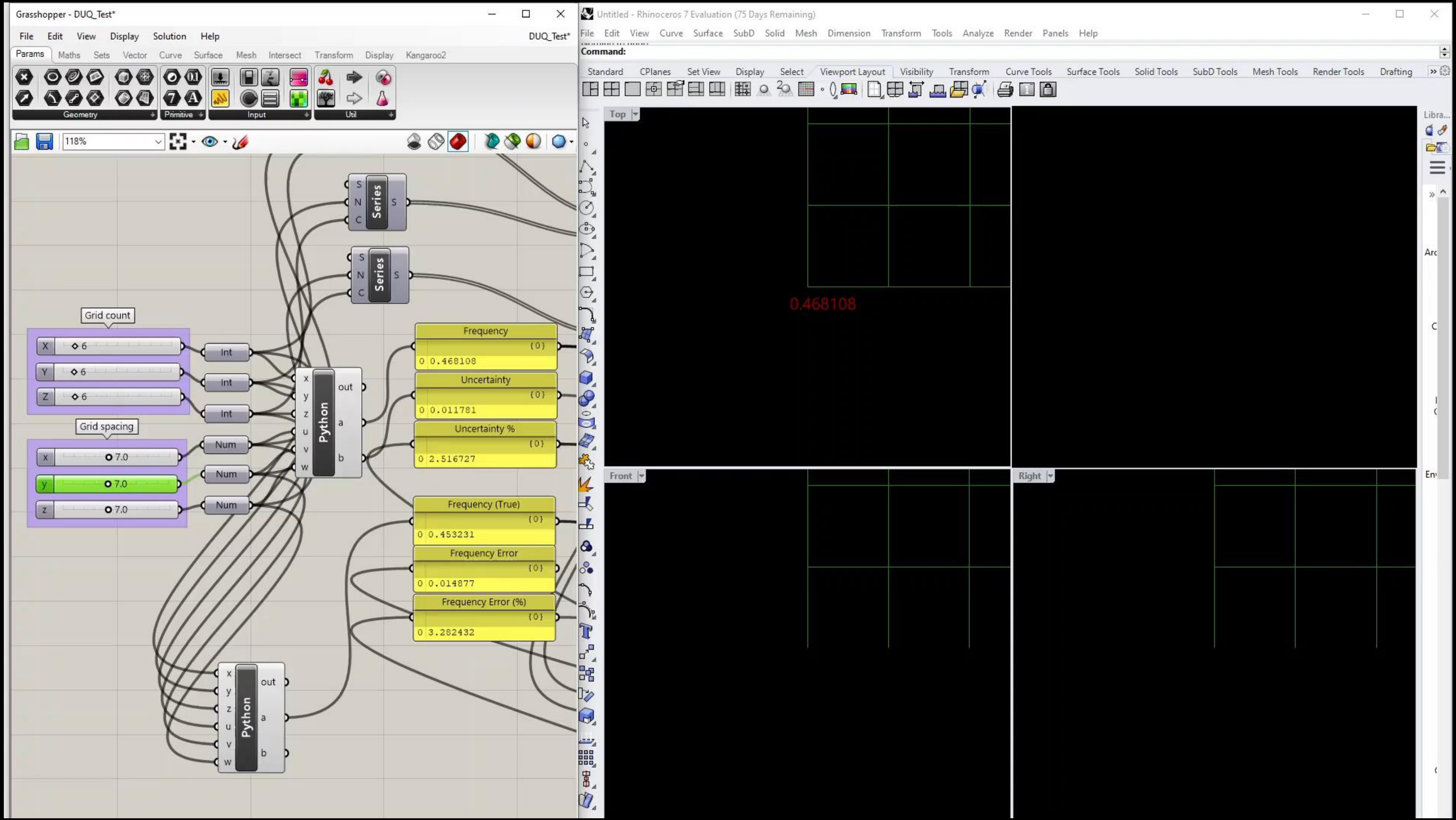




Results | Visualising Uncertainty

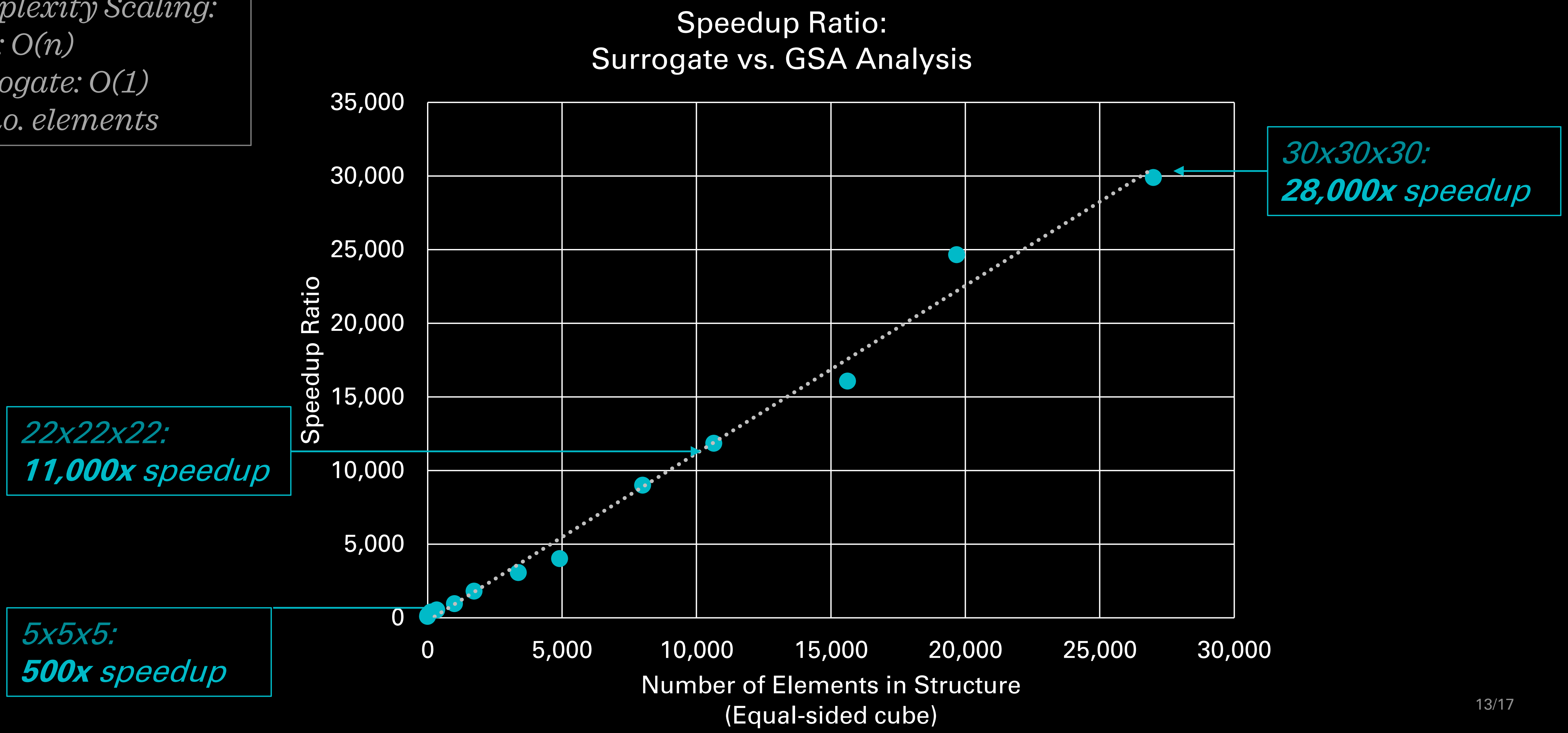


Results | Visualising Uncertainty – Grasshopper & Rhino

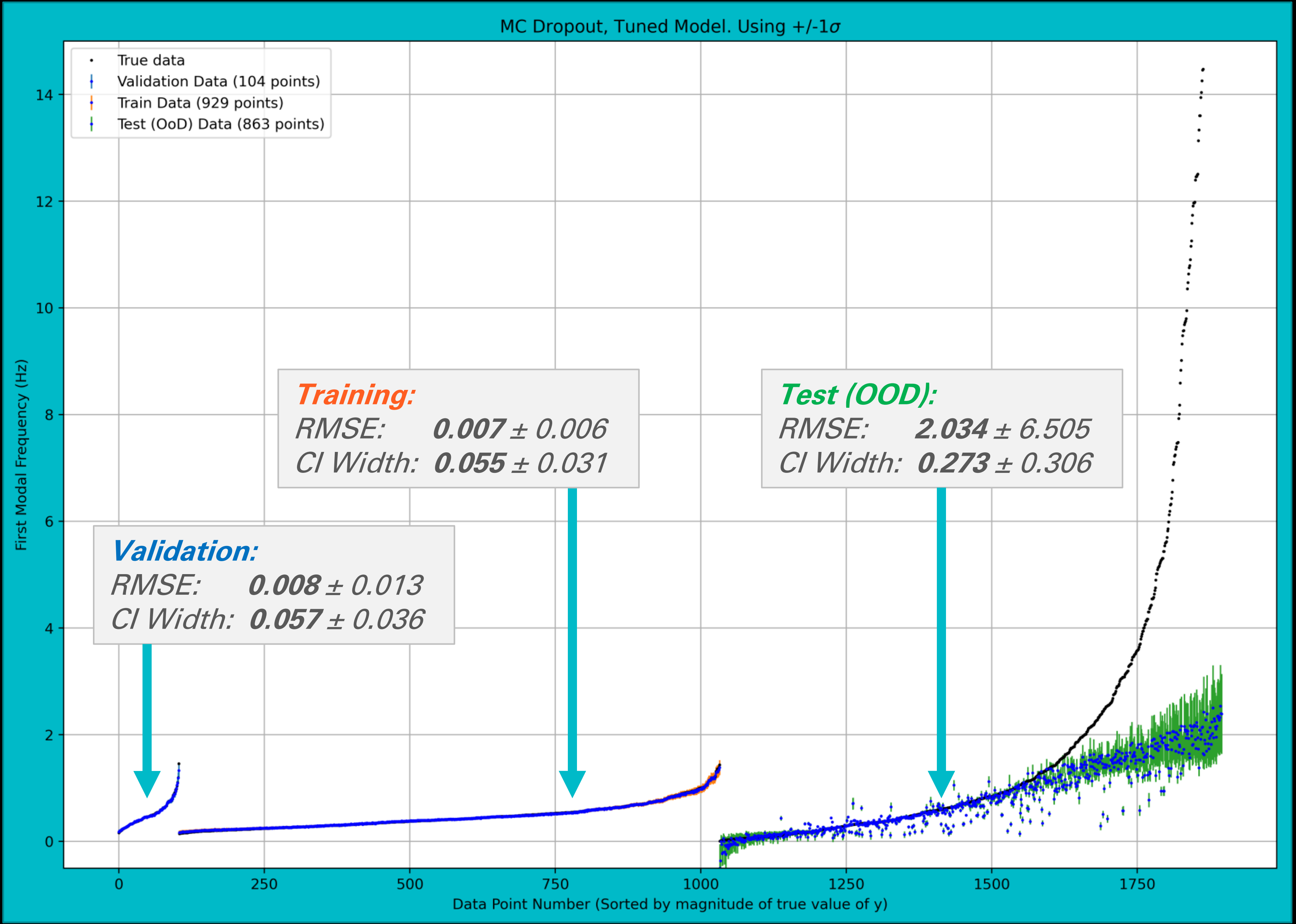


Results | Speed

Complexity Scaling:
GSA: O(n)
Surrogate: O(1)
n = no. elements



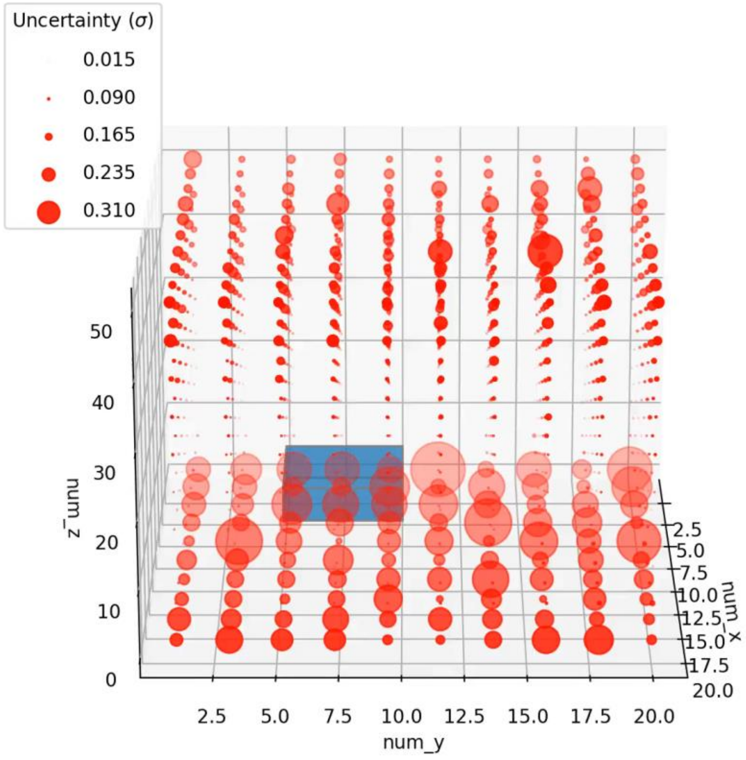
Results | Accuracy and Uncertainty: Reference Datasets



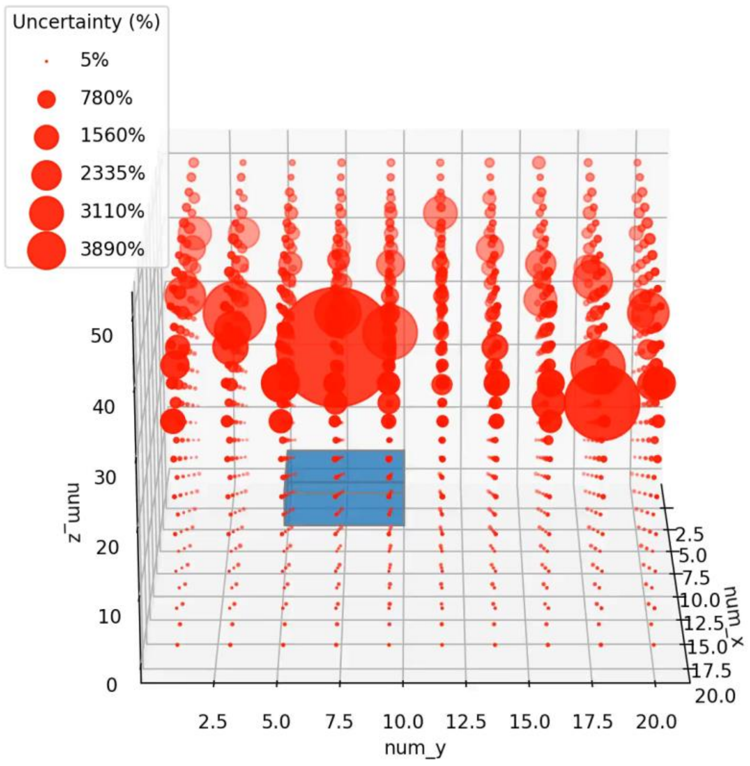
Results | Uncertainty - Unseen Geometries

Fixed: *length of elements in x, y, z*
Varying: *number of elements in x, y, z*

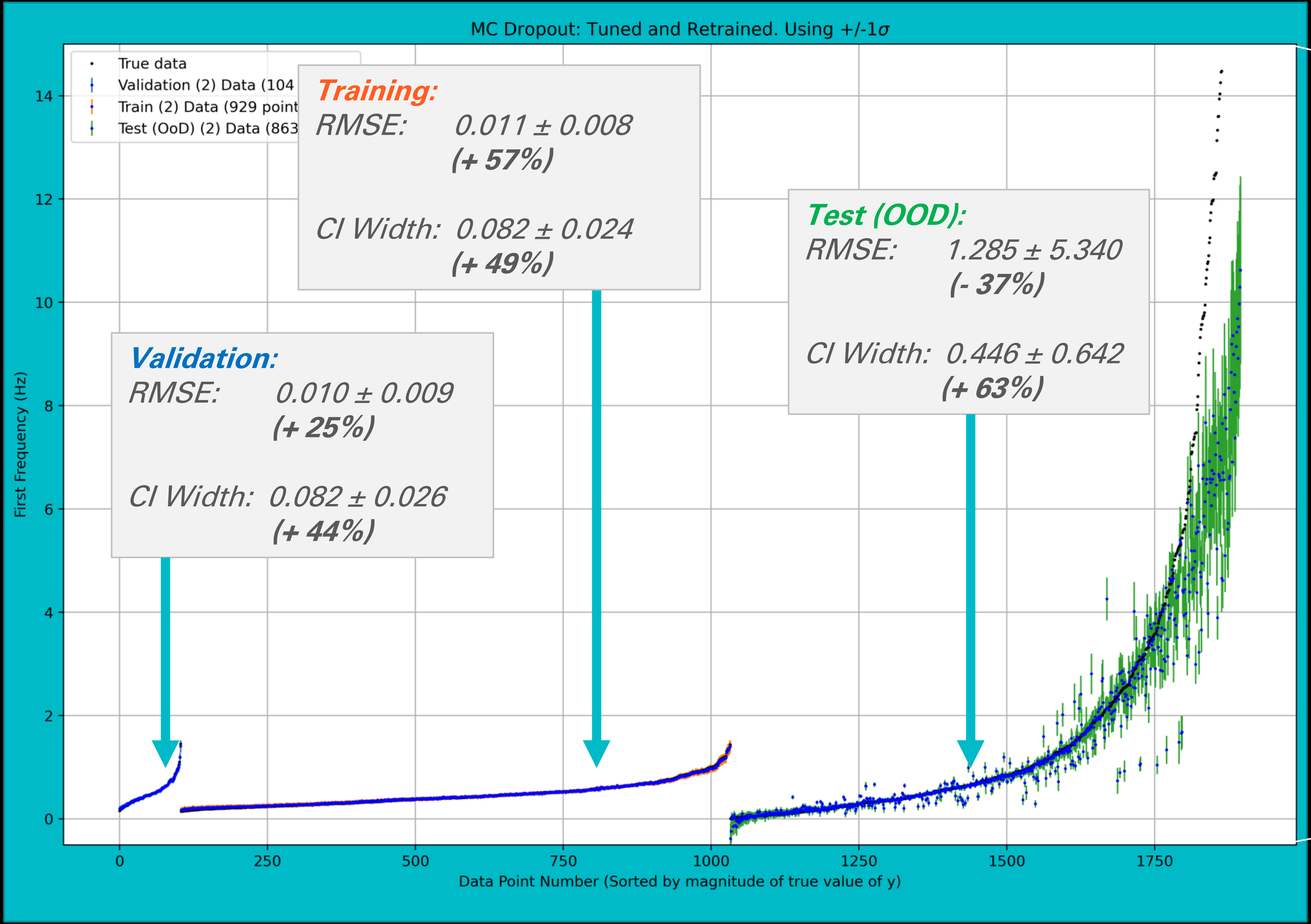
Absolute Uncertainty

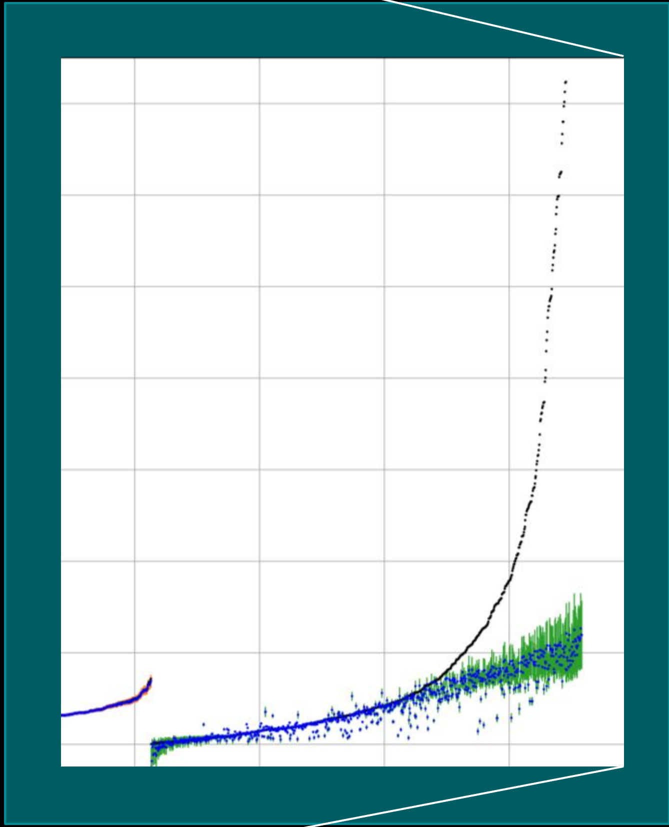


Relative (Percentage) Uncertainty

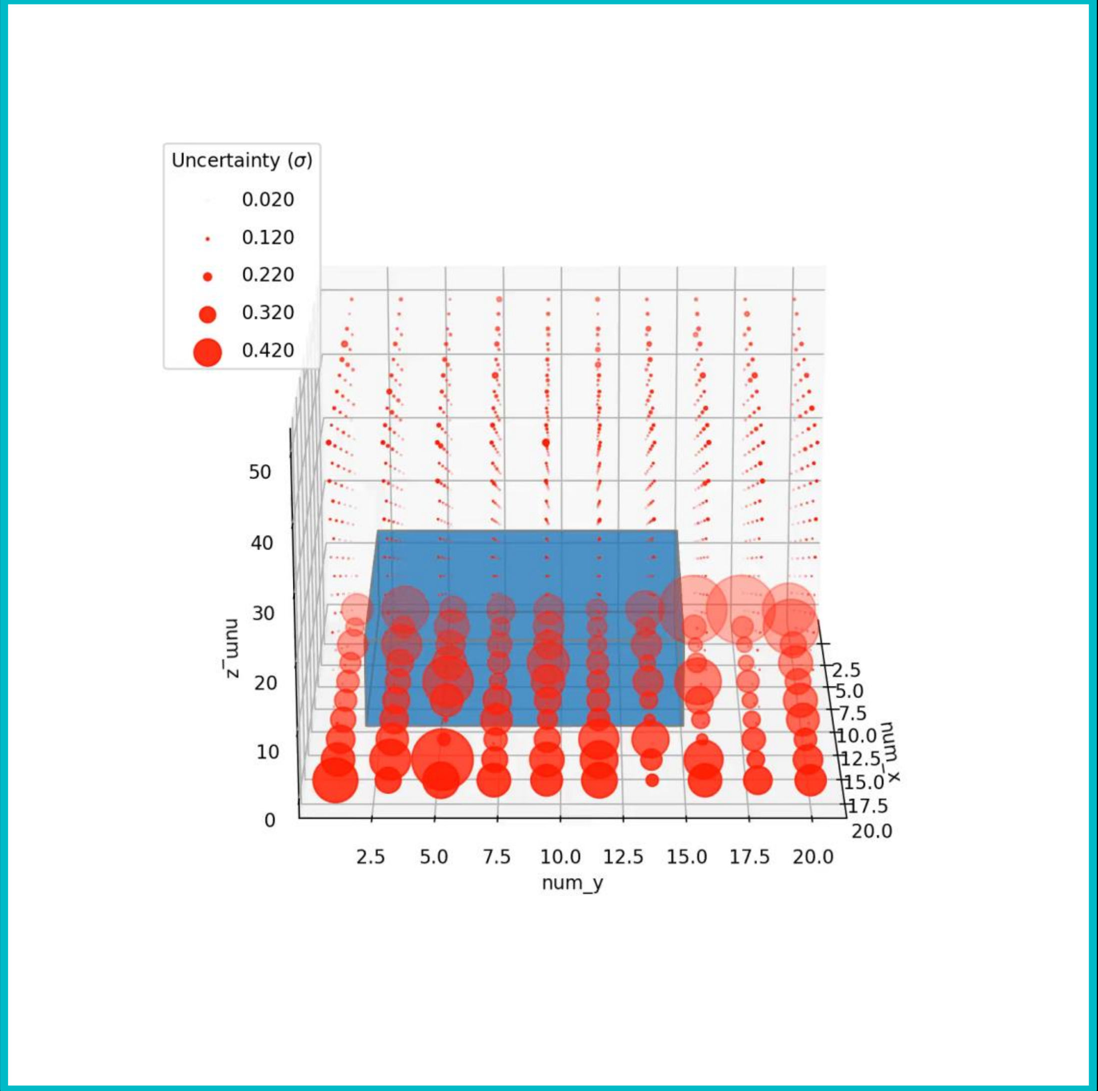


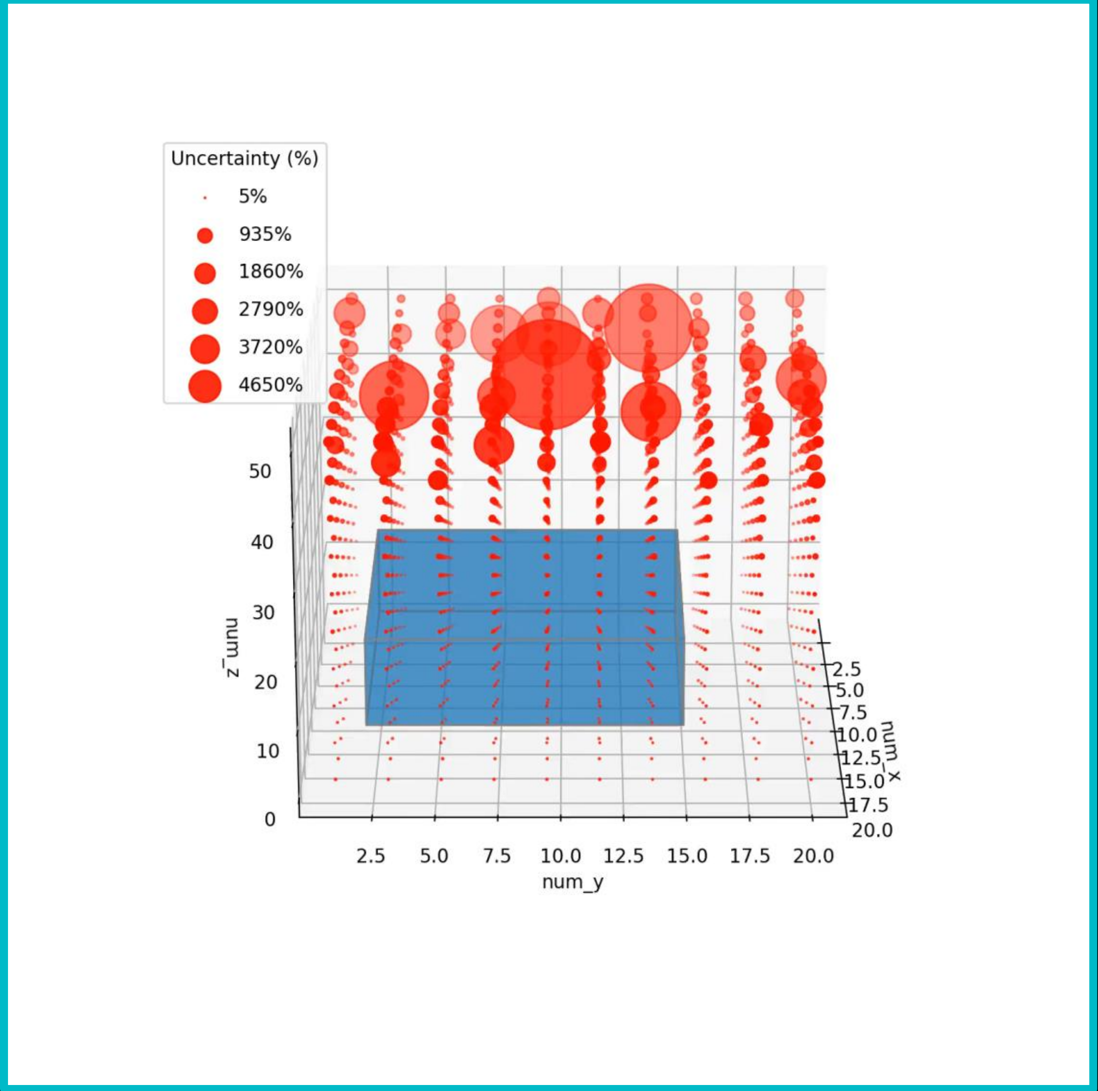
Results | Retraining With Additional Data





Results | Uncertainty - Unseen Geometries





Thank you for listening

Questions?