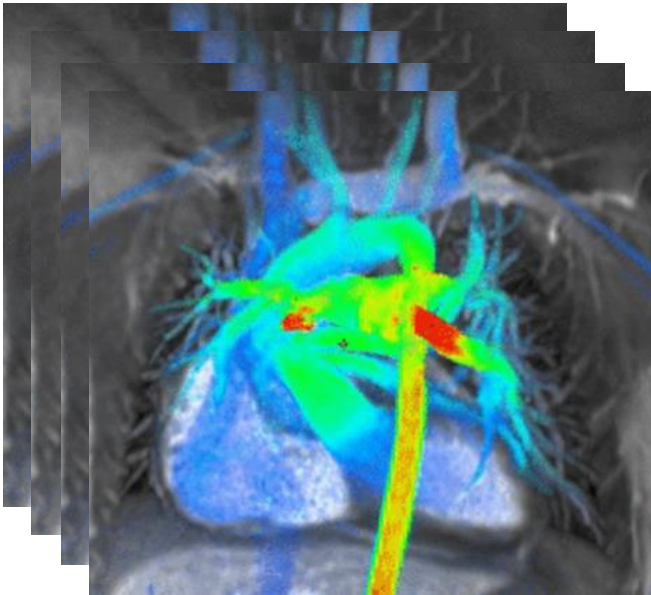


Jonas Kreidelmeyer, Johannes Stengele, Theresa Staufer, Florian Grüner, Rene Werner

4D-KI Track: Directed Diffusion of Colloidal Nanoparticles

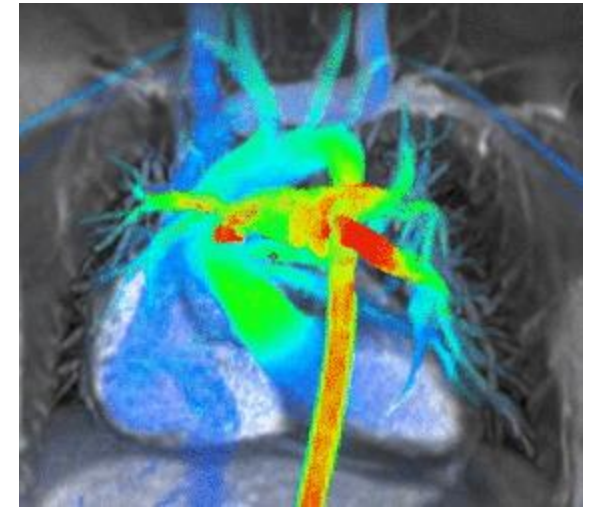
Background

4D KI Track



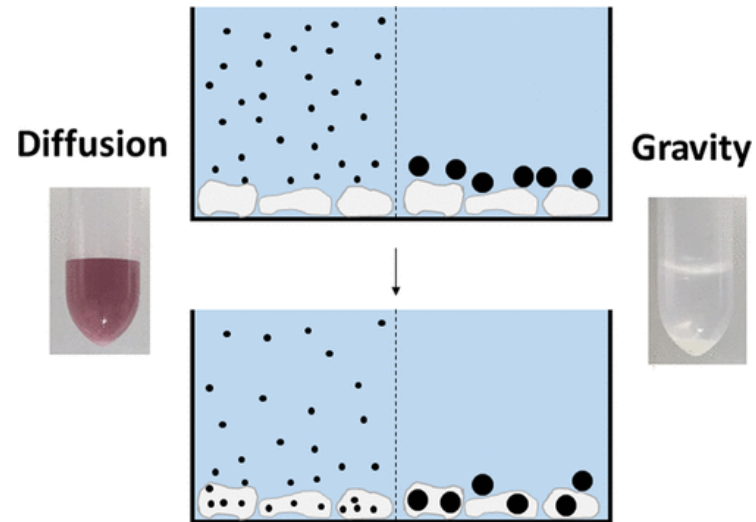
Temporally Sparse Data

Physics Informed Modelling



Fully 4D Output

Nanoparticle Diffusion

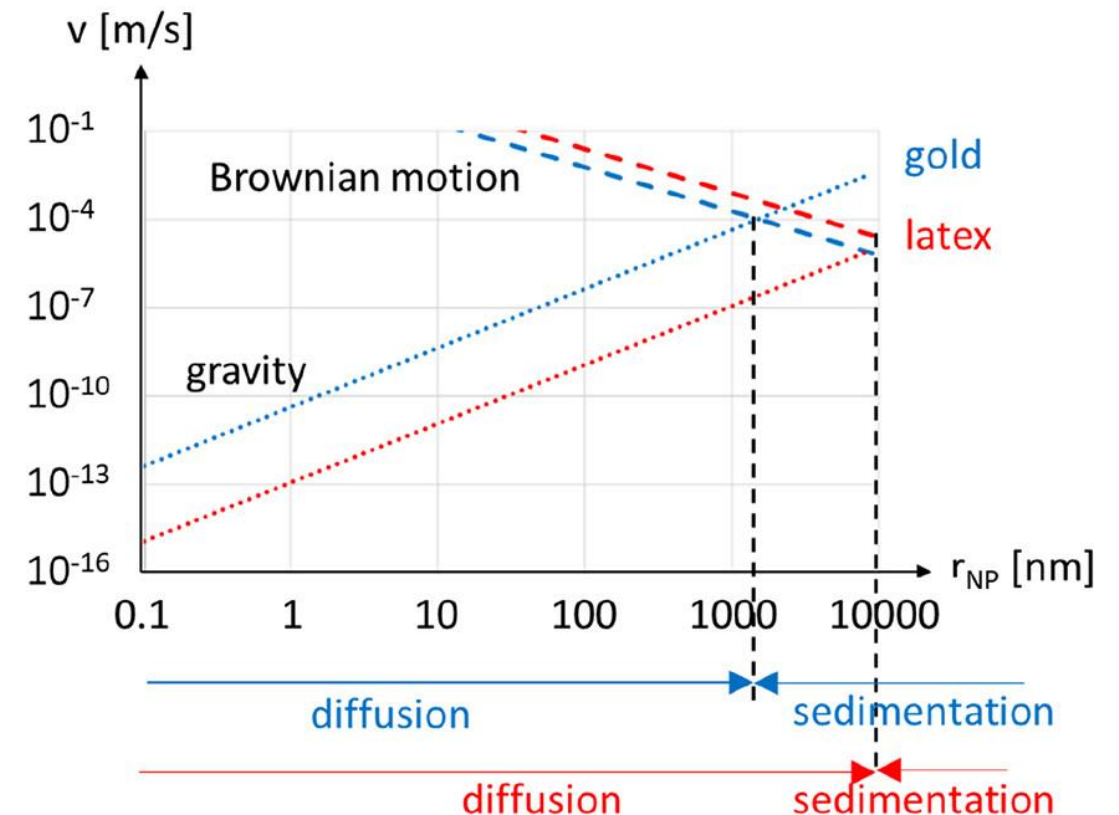


diffusion + gravity \rightarrow directed diffusion
 \Rightarrow good initial model system for biological processes

Previous work

- Feliu et al (2017) give analytical estimate of critical particle size for sedimentation
- Results do not match experiments

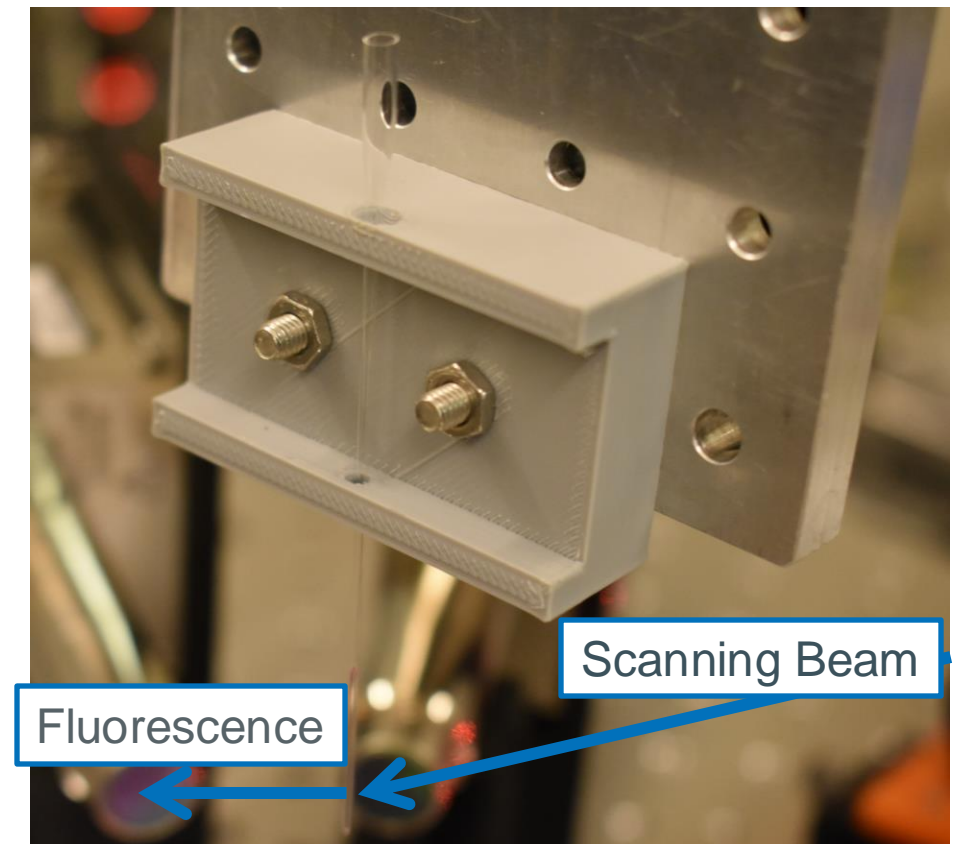
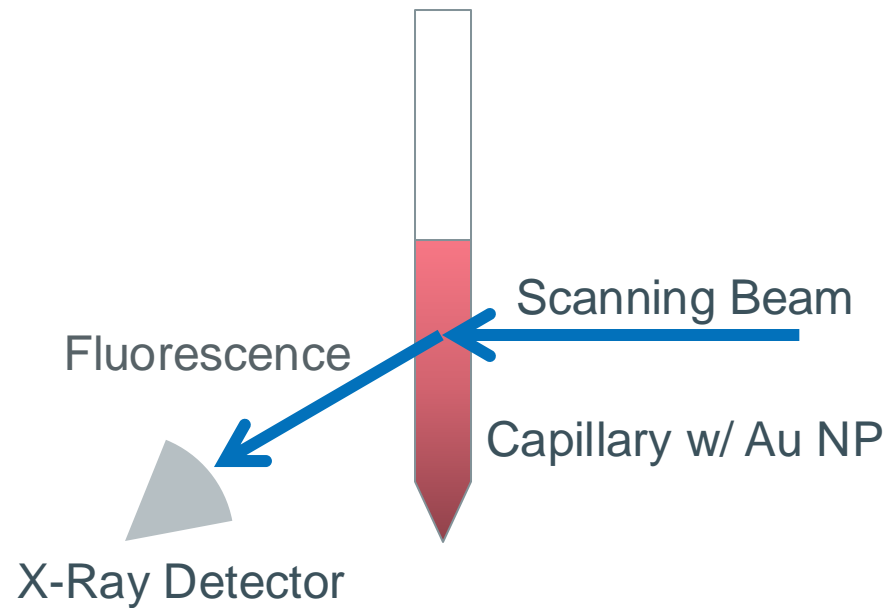
➡ Need to solve describing partial differential equation numerically



Thanks to:
Juan Barrios (providing samples)
Jannis Haak (measurement)
Florian Ziegler (measurement)

Measurement

Imaging Setup



Signal Model

- Total Signal proportional to tracer conc.
- Known fluor. energies and cross sections
- Fano noise on energy measurements
- Poisson noise on counts
- Smooth background

Directed Diffusion Model

- Concentration profile $c(x, t)$ obeys continuity: $\frac{\partial c}{\partial t} = -\frac{\partial J}{\partial x}$
- Flux J includes sum of diffusive and gravitational term

$$J_{\text{diff}} = -\frac{\lambda}{r_H} \frac{\partial c}{\partial x}$$

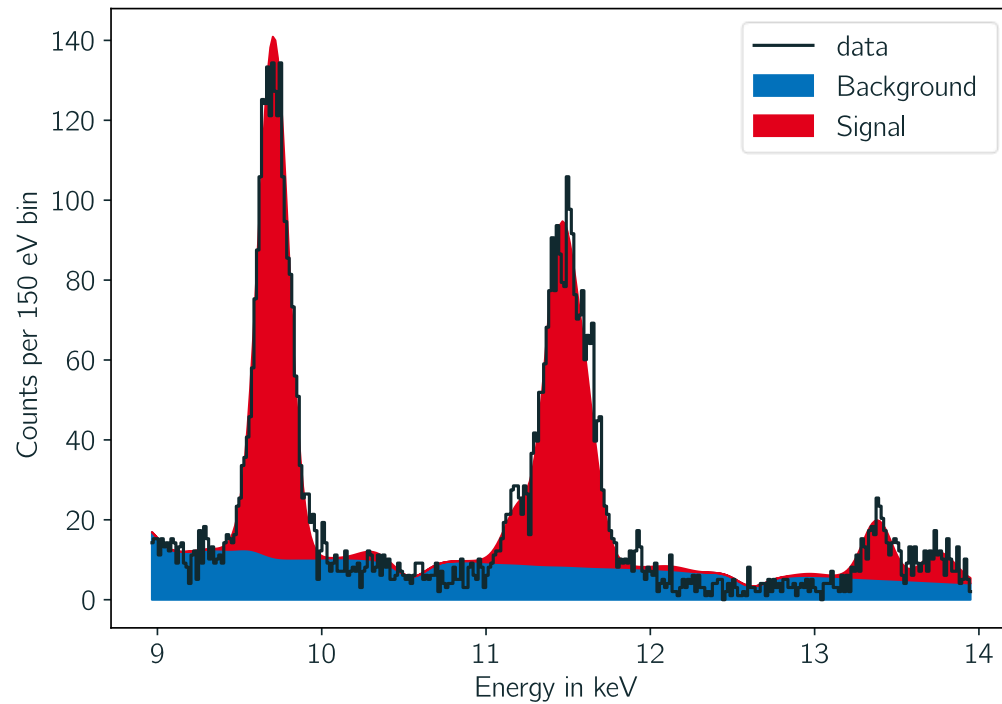
$$J_{\text{grav}} = \mu \frac{r_S^3}{r_H} c$$

- r_H - hydrodynamic radius
- r_S - solid radius
- $c(x, t)$ - concentration field
- λ, μ - apriori known constants

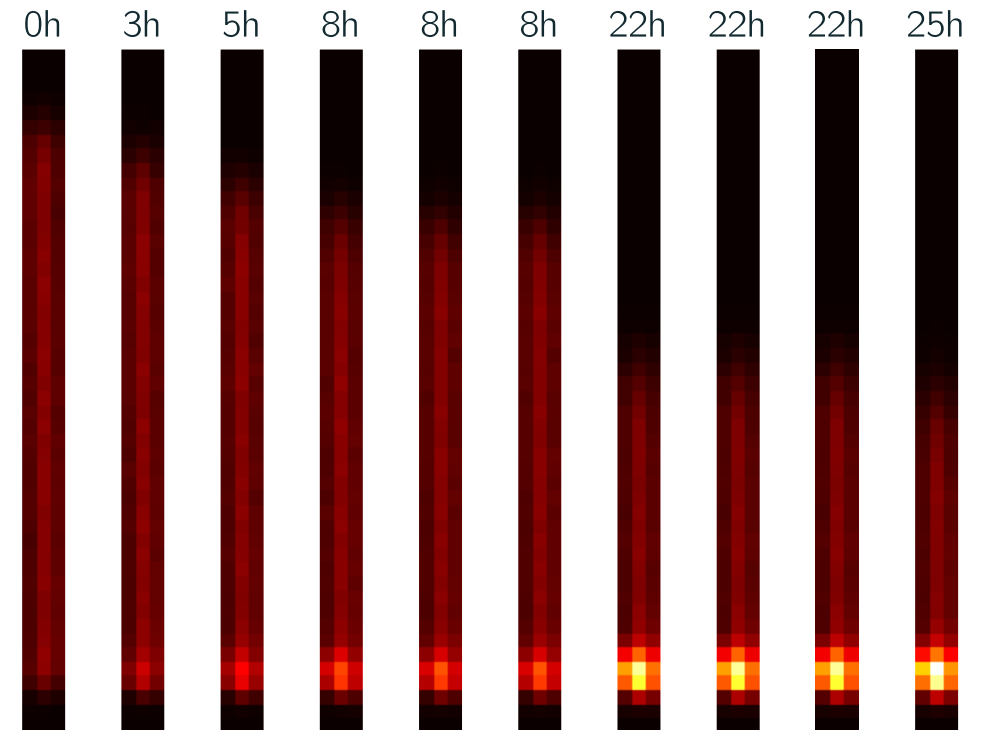
- Two counteracting effects:
 - Diffusion \longrightarrow homogeneous concentration profile
 - Gravity/Buoyancy \longrightarrow sedimentation and separation of solvent and solute

Tracer Quantification

Example of Single Point Spectrum



Scan Maps at Various Times



Physics Informed Modelling

Physics Informed Neural Networks

- Neural Networks trained to solve supervised learning task while respecting physical laws

$$\frac{\partial c}{\partial t} + \mathcal{N}_\nu[c] = 0, \quad x \in \Omega, \quad t \in [0, T]$$

$c(x, t)$ - unknown solution

$\Omega \subset \mathbb{R}^D$ - spatial domain

\mathcal{N}_ν - differential operator

ν - potentially unknown parameters

Measurement data $\{x_i, t_i, c_i\}_{i=1}^{N_{\text{data}}}$

Collocation points $\{x_j, t_j\}_{j=1}^{N_{\text{col}}}$

- Neural Network which outputs estimate

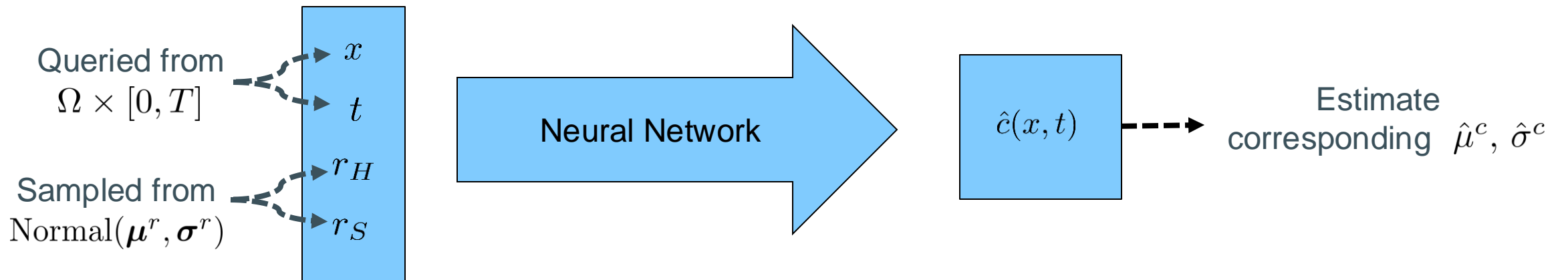
$$\hat{c}(x, t) = \text{NN}_\nu(x, t)$$

- Loss weighted sum of data term and PDE residual

$$\mathcal{L} = \mathcal{L}_{\text{data}} + \alpha \mathcal{L}_{\text{PDE}}$$

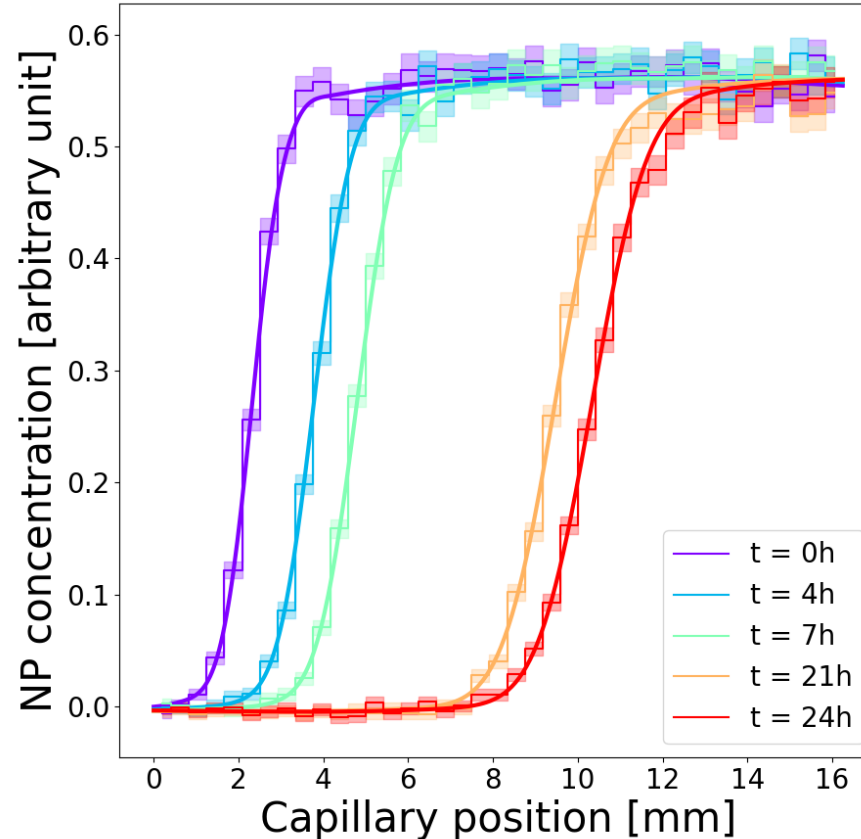
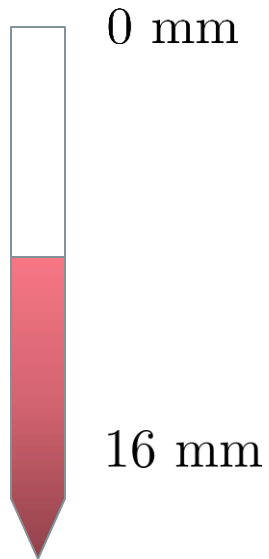
Stochastic Parameters and Output

- Estimate unknown solid and hydrodynamic radius, \mathcal{N}_ν with $\nu = \{r_H, r_S, \lambda, \mu\}$
- Data is subject to Gaussian noise $c_i \sim \text{Normal}(\mu_i^c, \sigma_i^c) \Rightarrow \{x_i, t_i, \mu_i^c, \sigma_i^c\}_{i=1}^{N_{\text{data}}}$
- Radii estimates with uncertainty $(r_H, r_S) \sim \text{Normal}(\boldsymbol{\mu}^r, \boldsymbol{\sigma}^r)$



- Train via Kullback-Leibler divergence
$$\mathcal{L}_{\text{data}} = \frac{1}{2N_{\text{data}}} \sum_{i=1}^{N_{\text{data}}} \left[\frac{(\mu_i^c - \hat{\mu}_i^c)^2}{\sigma_i^{c^2}} + \left(\frac{\hat{\sigma}_i^c}{\sigma_i^c} \right)^2 - \ln \left(\frac{\hat{\sigma}_i^c}{\sigma_i^c} \right)^2 - 1 \right]$$

4D Interpolation and Radii Estimates



- Continuous 4D interpolation in $\Omega \times [0, T]$
- $r_S, r_H \approx$ TEM and DLS measurement

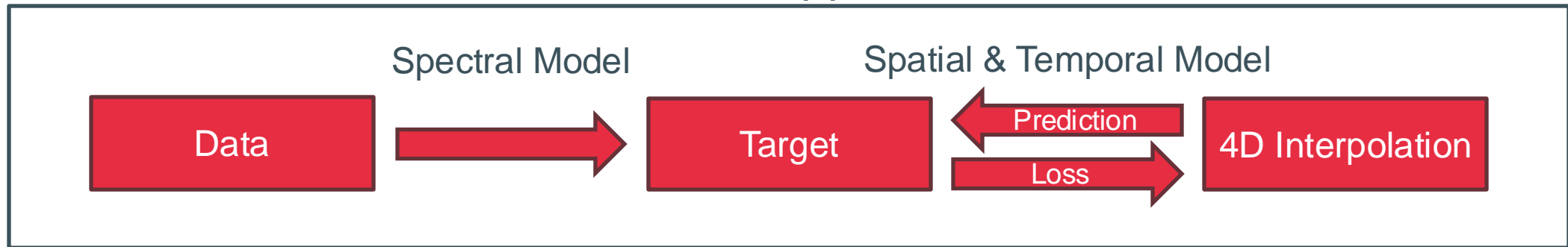
$$r_H = 48.1 \text{ nm} \pm 9.0 \text{ nm}$$

$$r_S = 47.7 \text{ nm} \pm 3.0 \text{ nm}$$

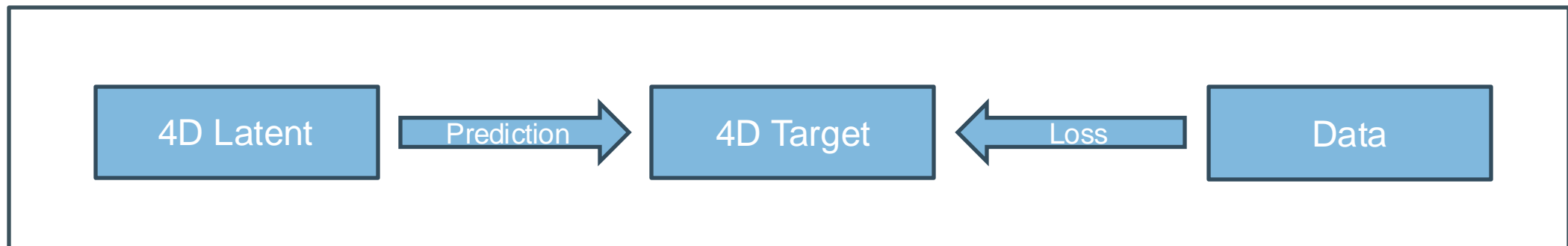
Outlook

Integration of Steps

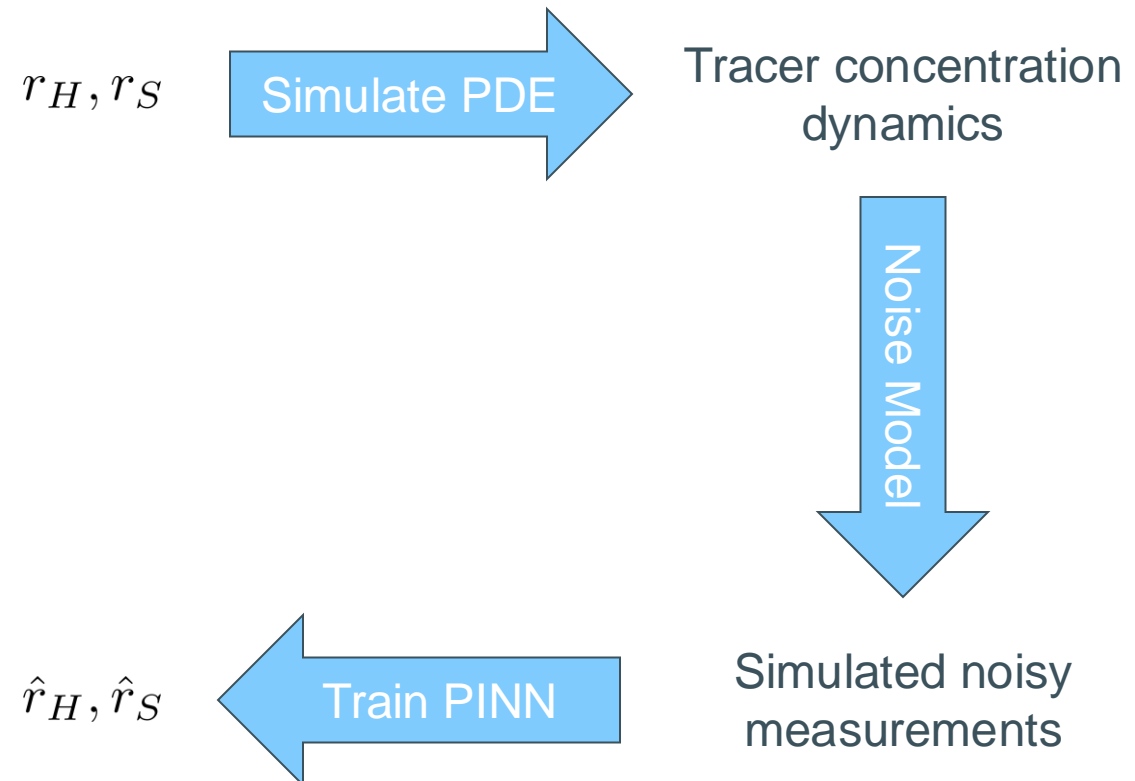
Current Approach



Generative Model



Simulations



What difference $\Delta r_{H/S} = r_{H/S}^{(1)} - r_{H/S}^{(2)}$
can we resolve?