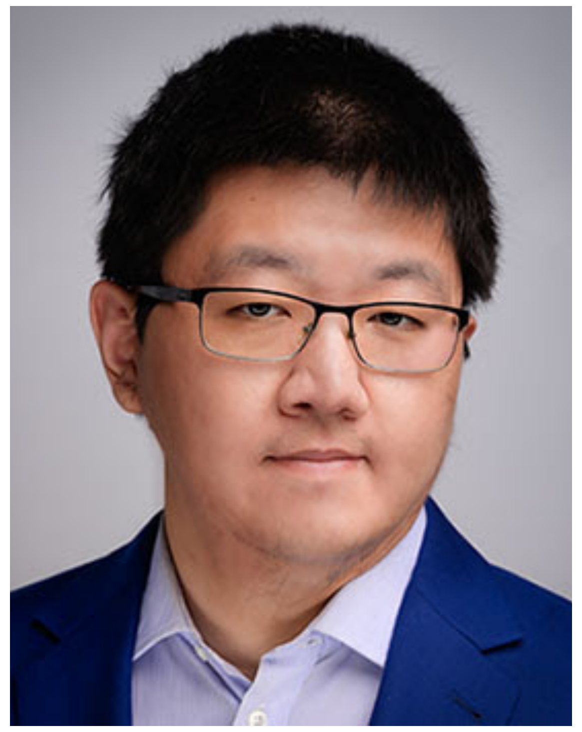
ICLR
International Conference On Learning Representations
Spotlight

Rare Event Surrogate Model (RESuM) for Physics Detector Design





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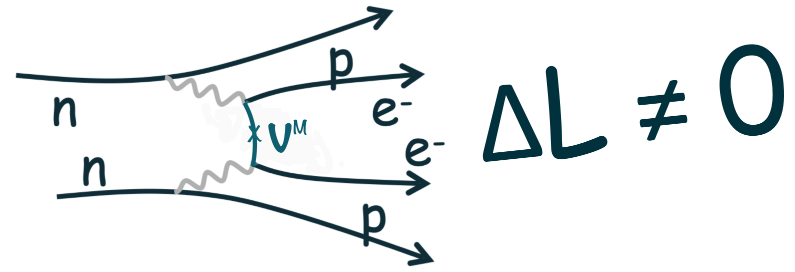
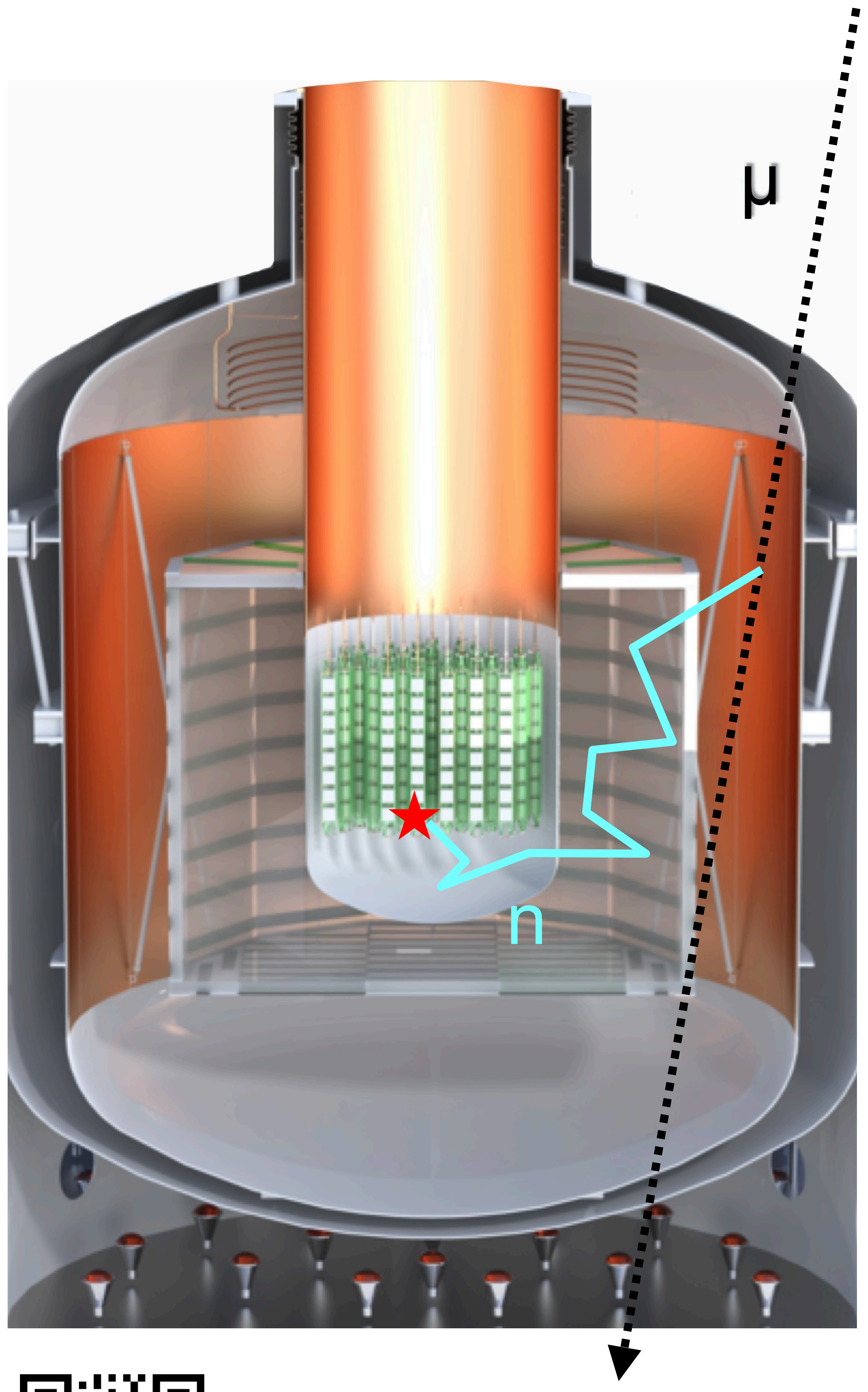
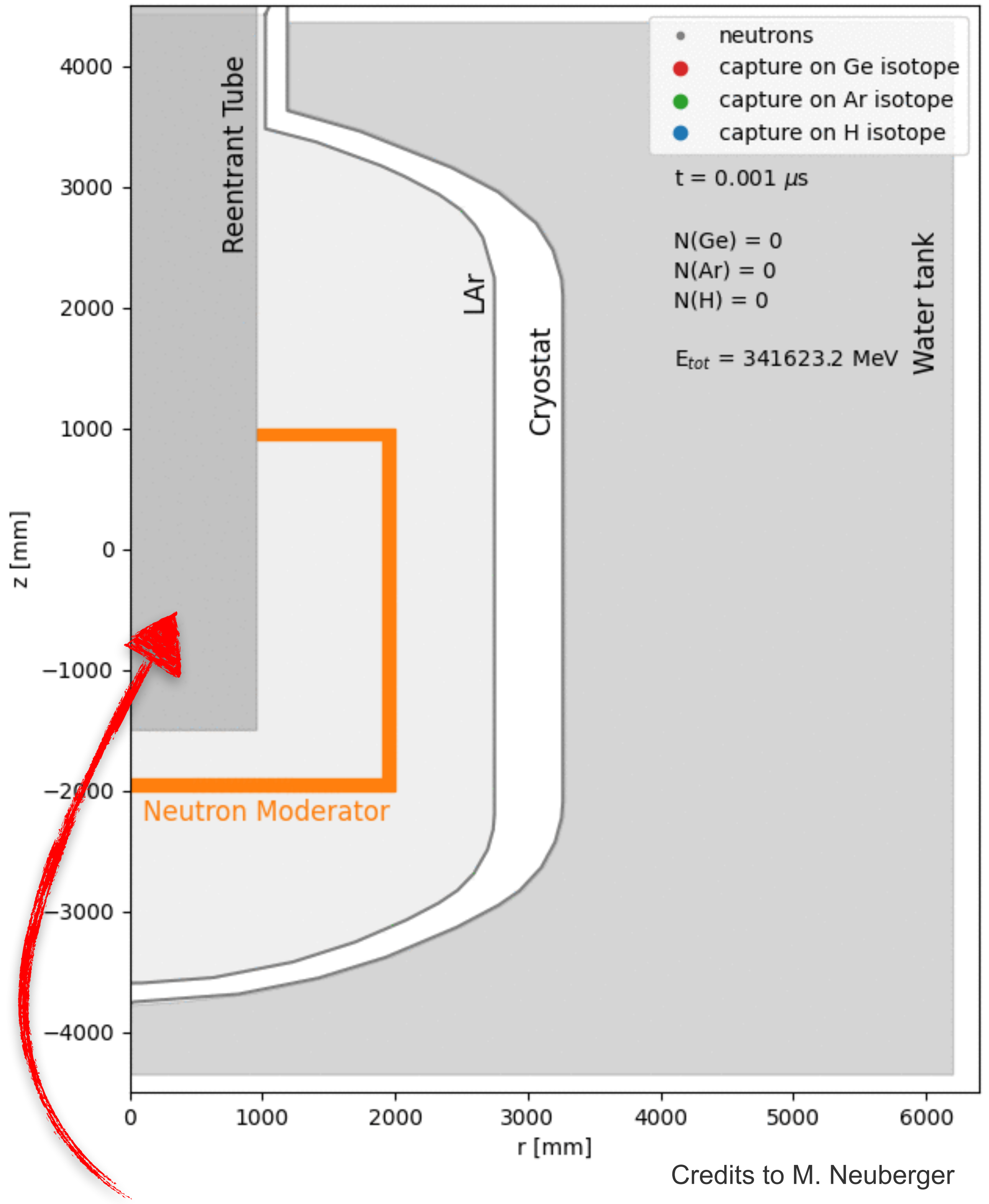
Poster

Github



Motivation - Physics Design Optimization





Credits to M. Neuberger

LEGEND

very rare dangerous event

- LEGEND proposed ton-scale experiment searching for ultra-rare neutrinoless double beta decay (a Nobel-prize-level discovery).
- Must suppress **extremely rare backgrounds** from cosmic muon-induced neutrons.
- Simulations are **expensive**, signal is **vanishingly rare.**
- Optimizing designs under such rare-event statistics is intractable.
- Need a rare event surrogate model for efficient, variance-aware optimization.

Rare Event Problem

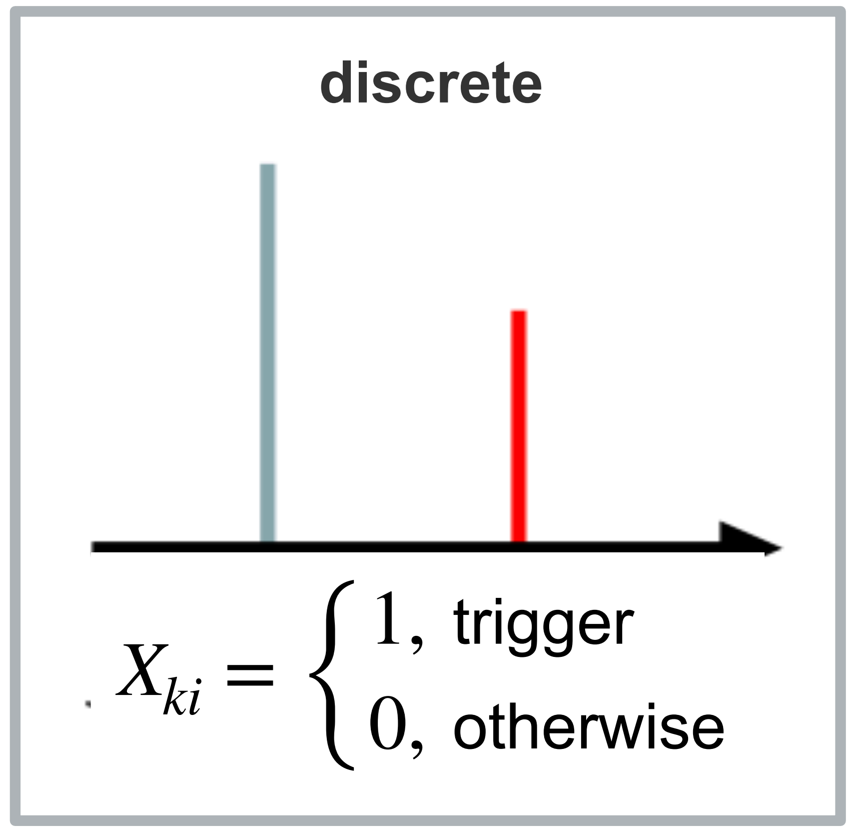
Event Simulation

N events with

- design parameter $\boldsymbol{\theta}_k$ and
- event-specific parameter $\boldsymbol{\phi}_{ik}$ (drawn from $g(\boldsymbol{\phi})$)

Event Outcome

X_{ik}



Signal trigger rate

$$y = \frac{1}{N} \sum X_{ik}$$

$$\sim \text{Poisson}(N\bar{t})/N$$

$$X_{ik} \sim \text{Bernoulli}(p = t(\boldsymbol{\theta}_k, \boldsymbol{\phi}_{ik}))$$

Trigger Probability

$t(\boldsymbol{\theta}_k, \boldsymbol{\phi}_{i,k})$ **small**

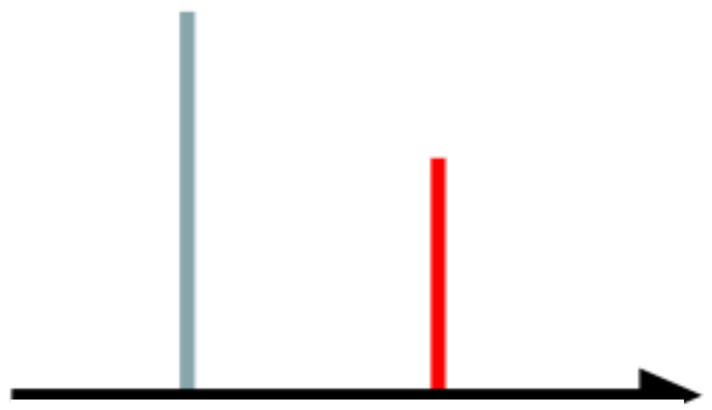
Rare Event Assumption

$$y \ll 1$$

Event Simulation
N events with
- design parameter $\boldsymbol{\theta}_k$ and
- event-specific parameter $\boldsymbol{\phi}_{ik}$ (drawn from $g(\boldsymbol{\phi})$)

Event Outcome
X_{ik}

discrete



$$X_{ki} = \begin{cases} 1, & \text{trigger} \\ 0, & \text{otherwise} \end{cases}$$

$$X_{ik} \sim \text{Bernoulli}(p = t(\boldsymbol{\theta}_k, \boldsymbol{\phi}_{ik}))$$

Trigger Probability
$t(\boldsymbol{\theta}_k, \boldsymbol{\phi}_{i,k})$ **small**

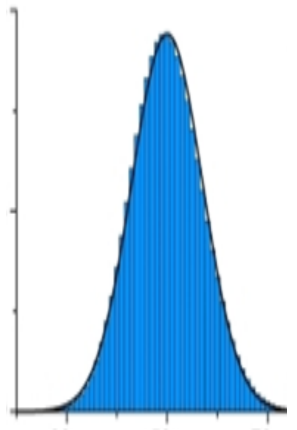
Signal trigger rate

$$y = \frac{1}{N} \sum X_{ik}$$

$$\sim \text{Poisson}(N\bar{t})/N$$

$$y \ll 1$$

Large N



Large N scenario

$$y \sim \mathcal{N}(\bar{t}(\boldsymbol{\theta}), \frac{\bar{t}(\boldsymbol{\theta})}{N})$$

Low Variance, High Cost.

$N \to \infty$, y will asymptotically approximate the **expected trigger probability**

$$\bar{t}(\boldsymbol{\theta}) = \int t(\boldsymbol{\theta}, \boldsymbol{\phi}) g(\boldsymbol{\phi}) \mathrm{d}\boldsymbol{\phi}$$

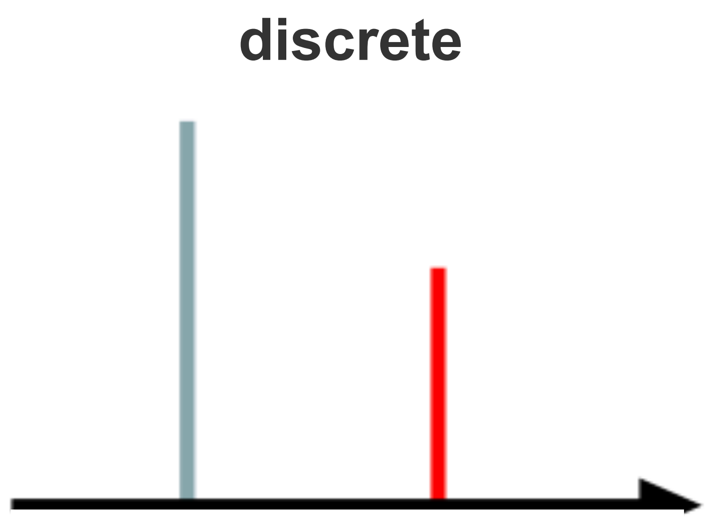
Ultimate metric to optimize

$$\boldsymbol{\theta}^\star = \arg\min_{\theta \in \Theta} \bar{t}(\boldsymbol{\theta})$$

Event Simulation
N events with

- design parameter $\boldsymbol{\theta}_k$ and
- event-specific parameter $\boldsymbol{\phi}_{ik}$ (drawn from $g(\boldsymbol{\phi})$)

Event Outcome
X_{ik}



$$X_{ki} = \begin{cases} 1, & \text{trigger} \\ 0, & \text{otherwise} \end{cases}$$

$$X_{ik} \sim \text{Bernoulli}(p = t(\boldsymbol{\theta}_k, \boldsymbol{\phi}_{ik}))$$

Trigger Probability
$t(\boldsymbol{\theta}_k, \boldsymbol{\phi}_{i,k})$ **small**

Signal trigger rate

$$y = \frac{1}{N} \sum X_{ik}$$

$$\sim \text{Poisson}(N\bar{t})/N$$

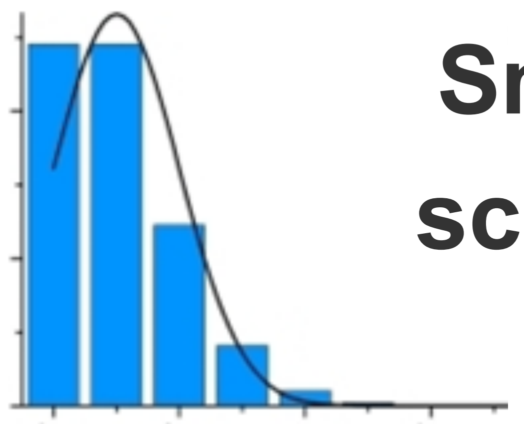
$$y \ll 1$$

Small N

Expensive simulator

Small N Scenario as simulation is costly:

- y very sensitive to statistical fluctuations.
- y takes **discrete values** and cannot be approximated by a normal distribution.

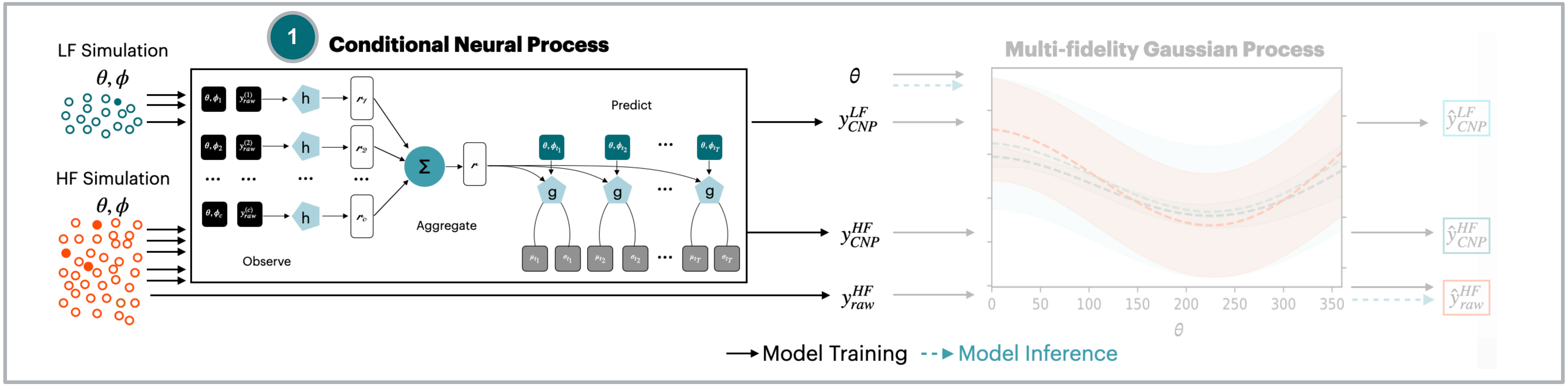


Small N scenario

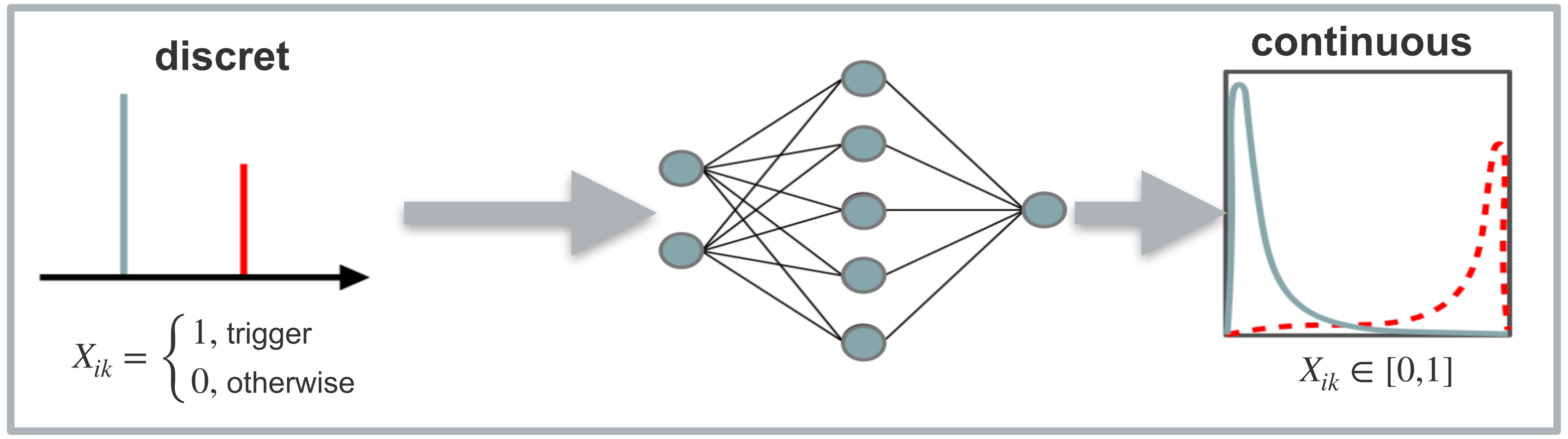
$y \in \{0/N, 1/N, \ldots\}$ discrete

High Variance, Low Cost.

Rare Event Surrogate Model (ReSUM)



1. Conditional Neutral Process



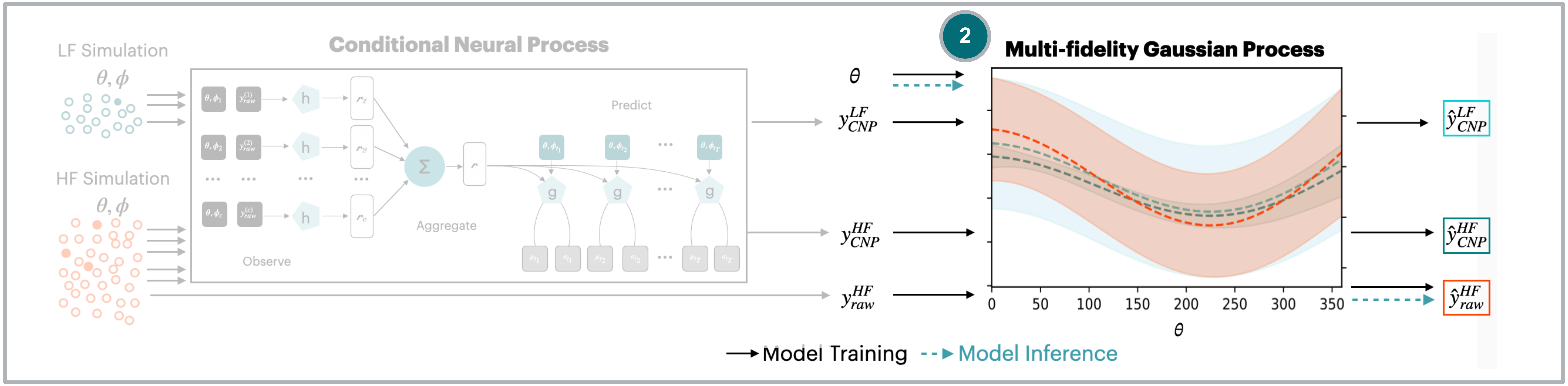
$X_{ik} = \begin{cases} 1, \text{trigger} \\ 0, \text{otherwise} \end{cases}$

$X_{ik} \in [0,1]$

Mitigate statistical noise

- Converts each discrete event outcome into a continuous score
- Propagates uncertainty awareness into final mapping

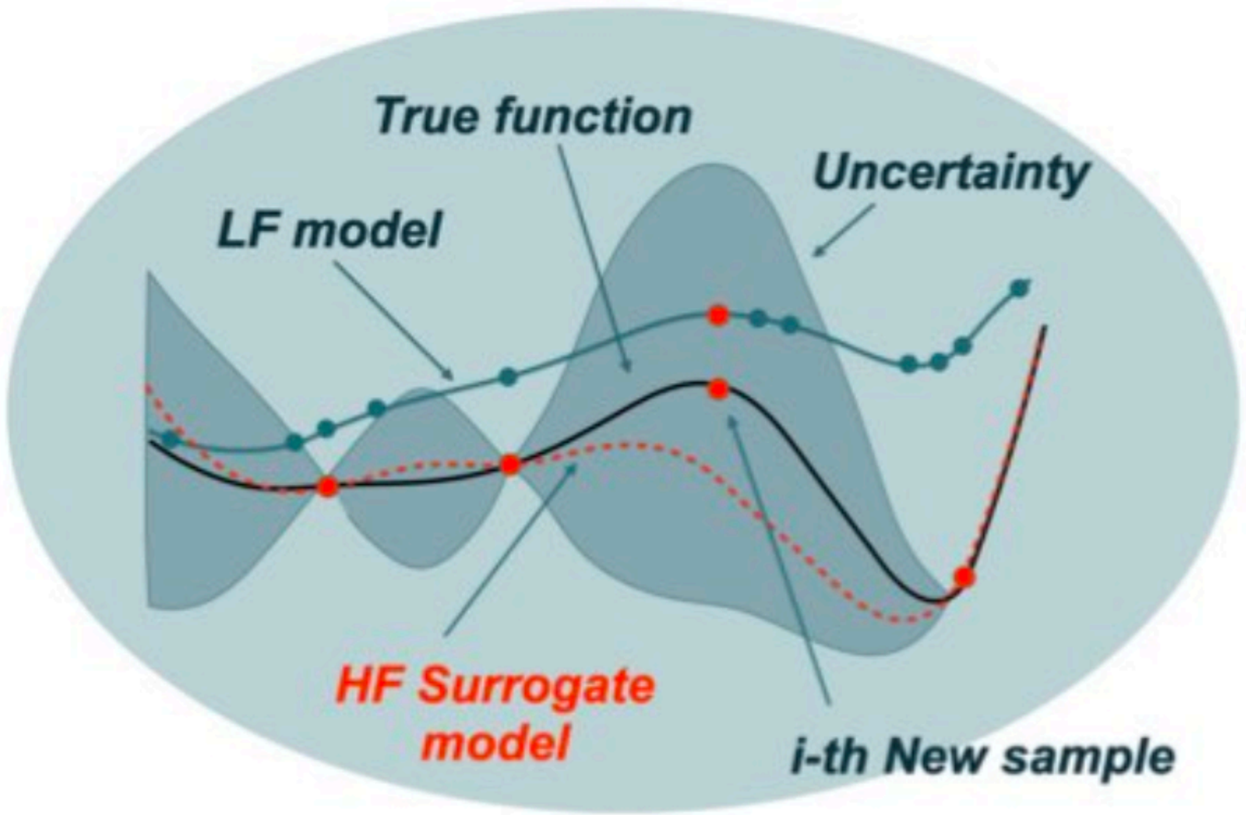
Rare Event Surrogate Model (ReSUM)



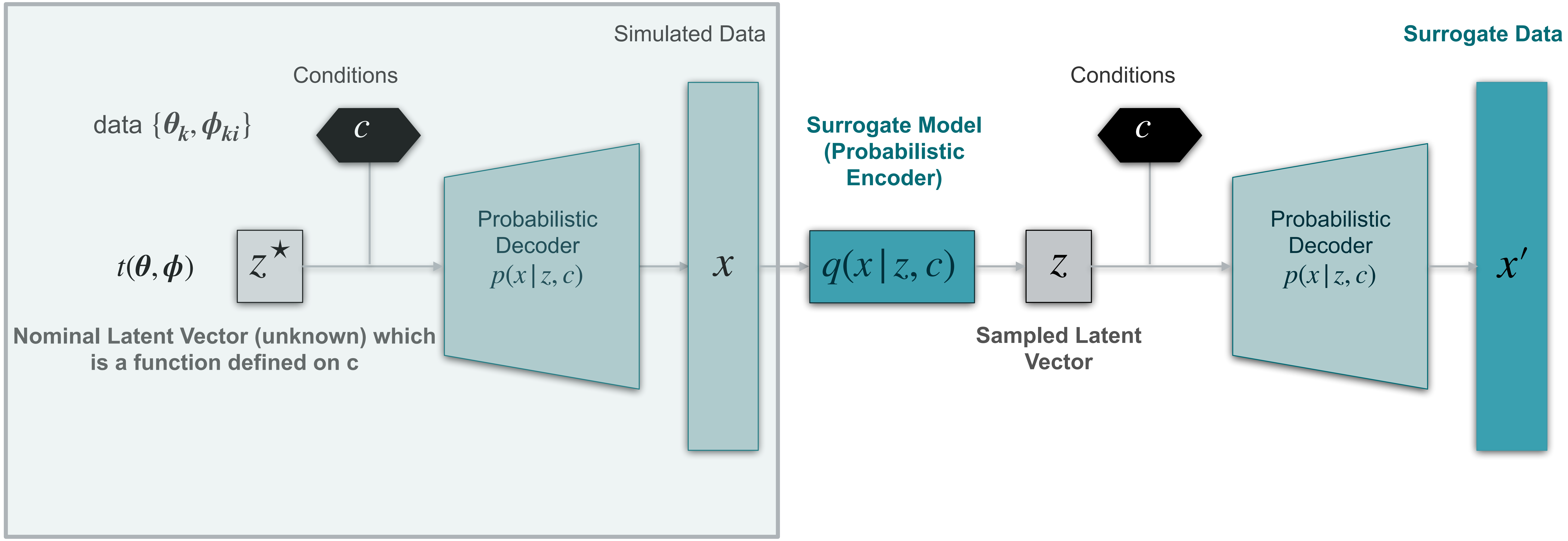
2. Multi-fidelity Gaussian Process

Reduce computational cost

- Multi-Fidelities approach where low-fidelity (LF) helps with space exploration



Rare Event Problem as Probabilistic Model



Bernoulli process acts as probabilistic decoder

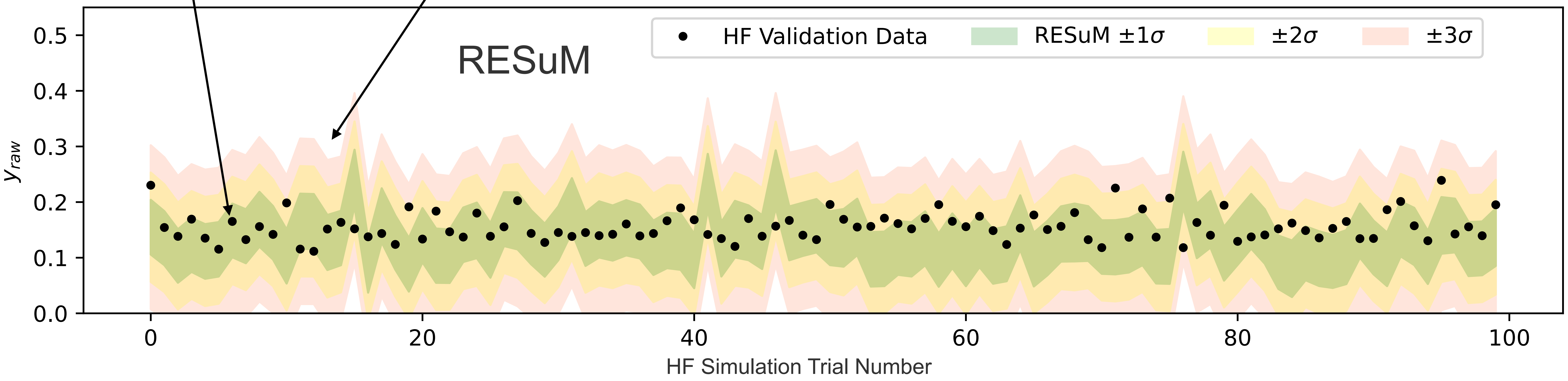
Posterior distribution $q(t(\theta, \phi))$ serves as probabilistic encoder

Model Benchmarking

- **96.7% reduction in compute cost**
- **Accurate and calibrated predictions**

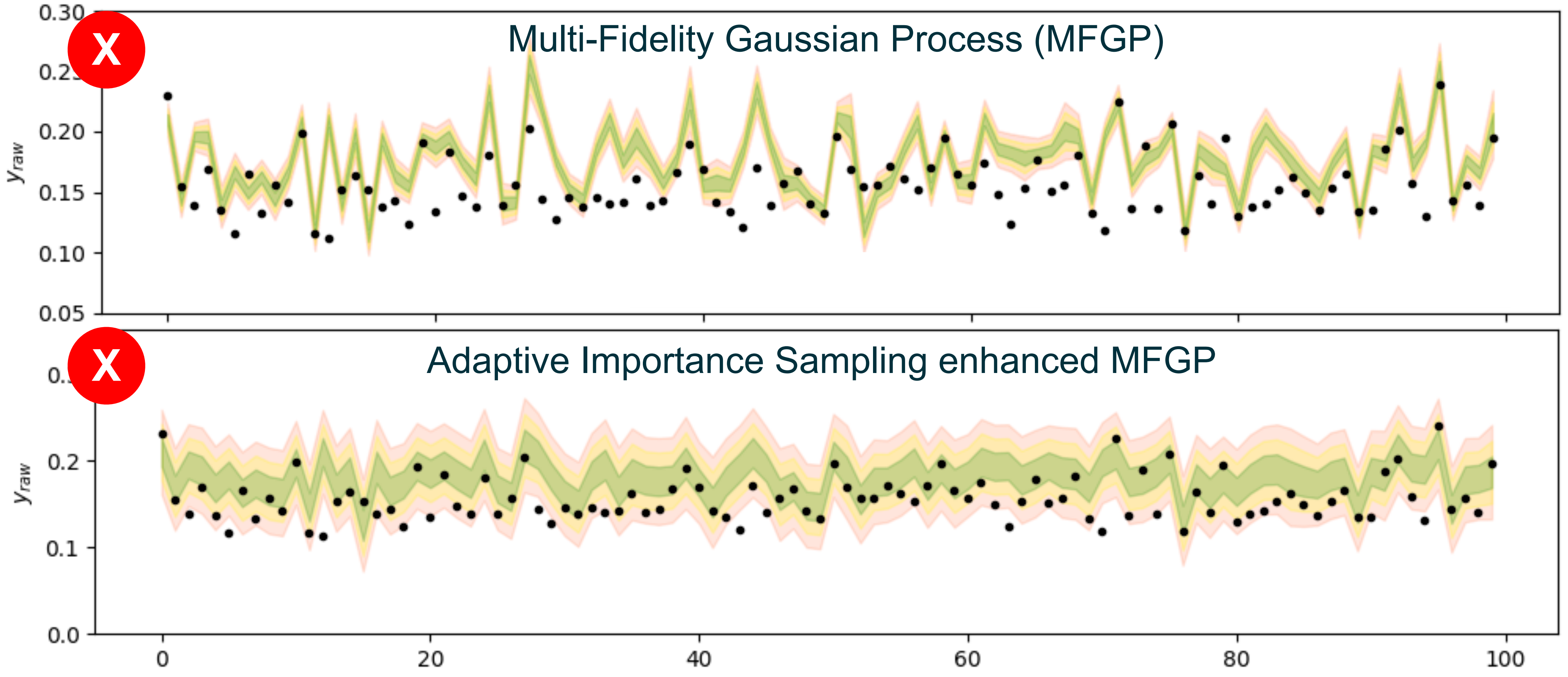
• independent 100 HF simulation for validation

model prediction



Benchmarking Result of RESuM model with respect to different baseline models.

- Overly narrow prediction bands
- Poor alignment
- Predictions lack physical relevance



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More details in the paper

Rare Event Surrogate Model (RESuM) for Physics Detector Design

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Poster Session
April 25th, 12 - 2:30 am PDT

Thank you for the support by U.S. DOE, LBNL, NERSC, UCSD, SDSC, LEGEND, the BUQ Group, Yue Ma and Yian Ma.