

Multi-Fidelity Emulation for matter power spectrum and Ly α flux power spectrum

Cosmology from Home 2022

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Multi-fidelity emulation for matter power spectrum using Gaussian processes
Ming-Feng Ho^{1,3}, Simeon Bird¹, Christian R. Shelton² (2022 MNRAS)
arXiv:2105.01081

A multi-fidelity emulator for Ly α forest
Martin Fernandez^{1,4}, Ming-Feng Ho^{1,3}, Simeon Bird¹ (in prep)

Multi-fidelity emulation using simulation from different boxsizes
Ming-Feng Ho^{1,3}, Simeon Bird¹, Christian R. Shelton² (in prep)

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PHYSICS &
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Cosmology from Home

Outline

- What's the problem? Why multi-fidelity
- What's emulation?
- What's multi-fidelity?
- Example 1: matter power spectrum
- Example 2: emulation for different simulation box sizes
- Example 3: Ly α 1-D flux power

Why multi-fidelity emulation?

Problem of current emulation

- **Problem:** As the simulations become increasingly more **realistic & expensive**, the simulation data needed to train an accurate emulator can be **difficult to generate**.
- EuclidEmulator2 (2020): **needs 200+ simulations (3000³)** in 8D even though using Latin hypercube
- And we need to emulate beyond Λ CDM in the future ... (more dimensions!)

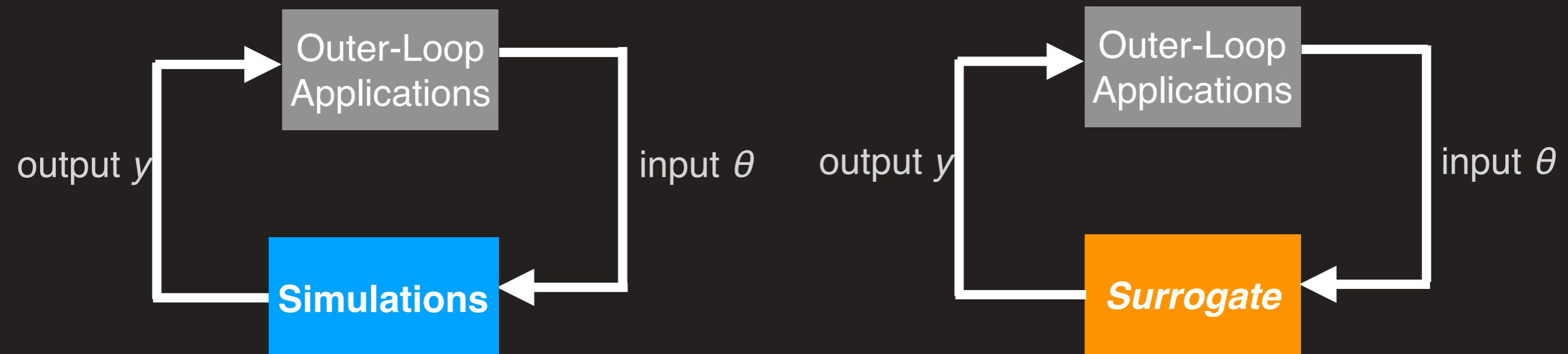
*Emulator: A model learns the mapping relationship from cosmological parameters θ to summary statistics (e.g., matter power spectrum) through a statistical learning process

What's emulation?

Cosmic calibration

- History: analytical calculation is not enough anymore for future surveys, we have to rely on numerical simulations to give accurate theoretical predictions ...
- Key ingredients for emulation:
 - Experimental design: space filling
 - Surrogate modelling: interpolation

- Outer-loop applications:
 - Uncertainty quantification
 - Inference
 - Optimization



What's emulation? ~~Cosmic calibration~~

Bayesian calibration for computer experiments

- History: analytical calculation is not enough anymore for future surveys, we have to rely on numerical simulations to give accurate theoretical predictions ...
- Key ingredients for ~~emulation~~ *Bayesian* modelling:
 - Experimental design: ~~space-filling~~ **Data**
 - Surrogate modelling: ~~interpolation~~ **Prior**

Emulation =

Posterior predictions given *Prior* and *Data* ^{Simulations}



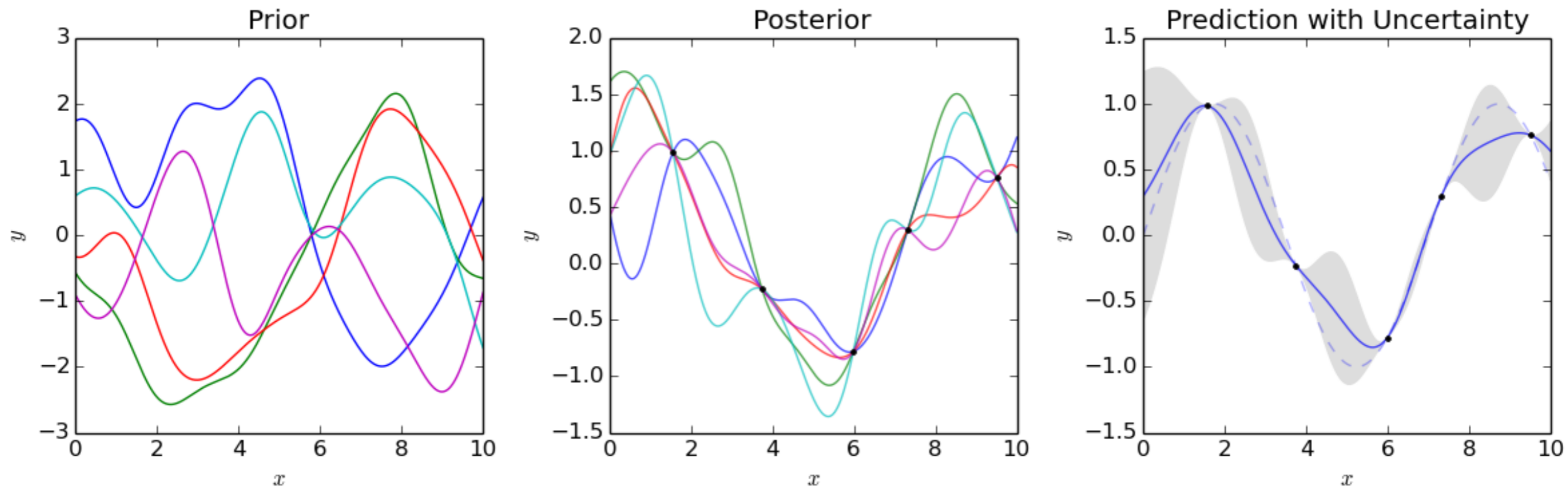
Simulations you haven't run



A distribution over smooth functions



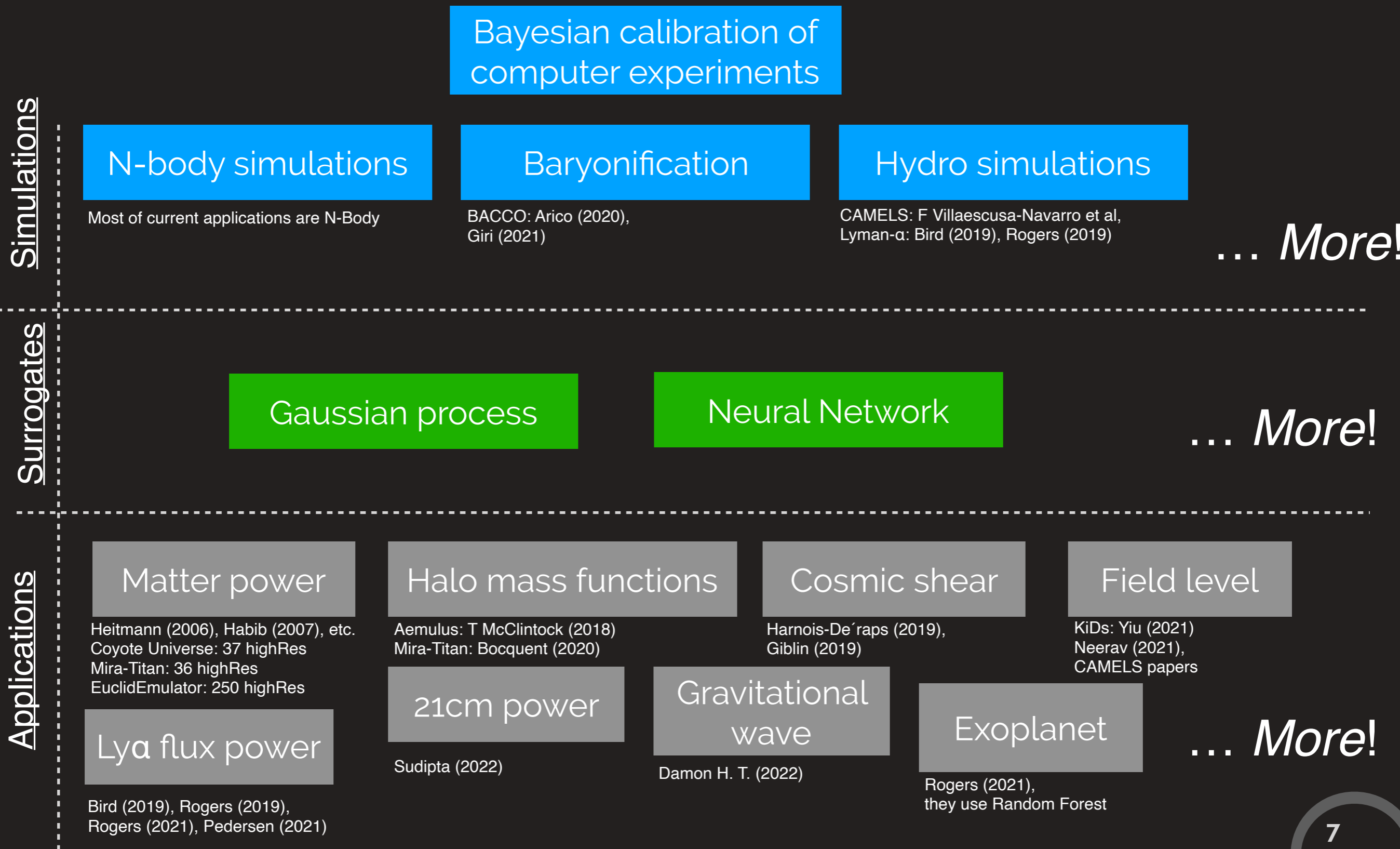
Gaussian process: Bayesian function prediction



- Gaussian process prior: Smoothness and monotonicity features of $y(x)$ before data are collected.
- Bayesian approach: Choose a flexible prior allowing many shapes of $y(x)$, and let the Bayesian machinery to direct the details of the predictions.*

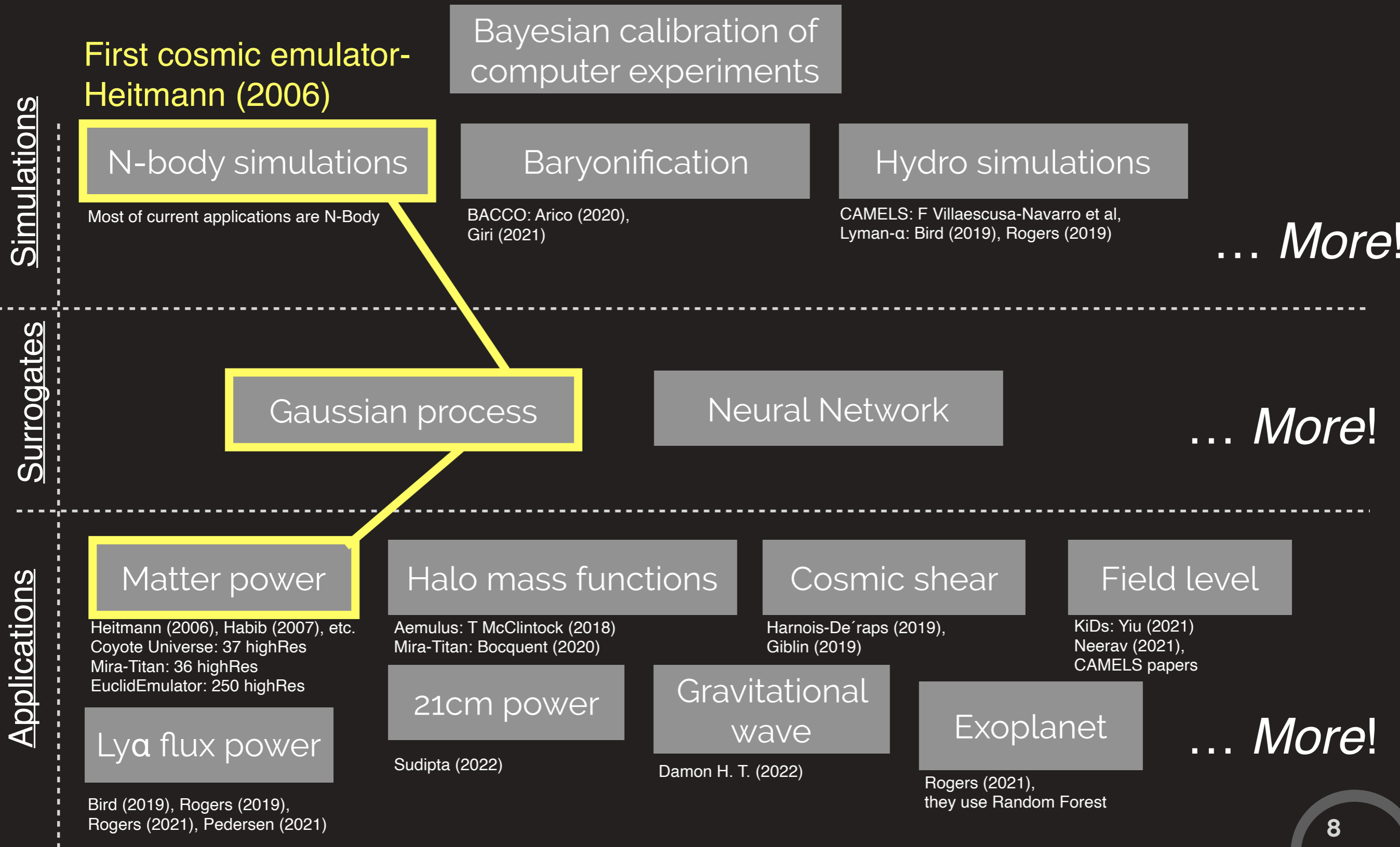
What's emulation?

Roadmap of building an emulator



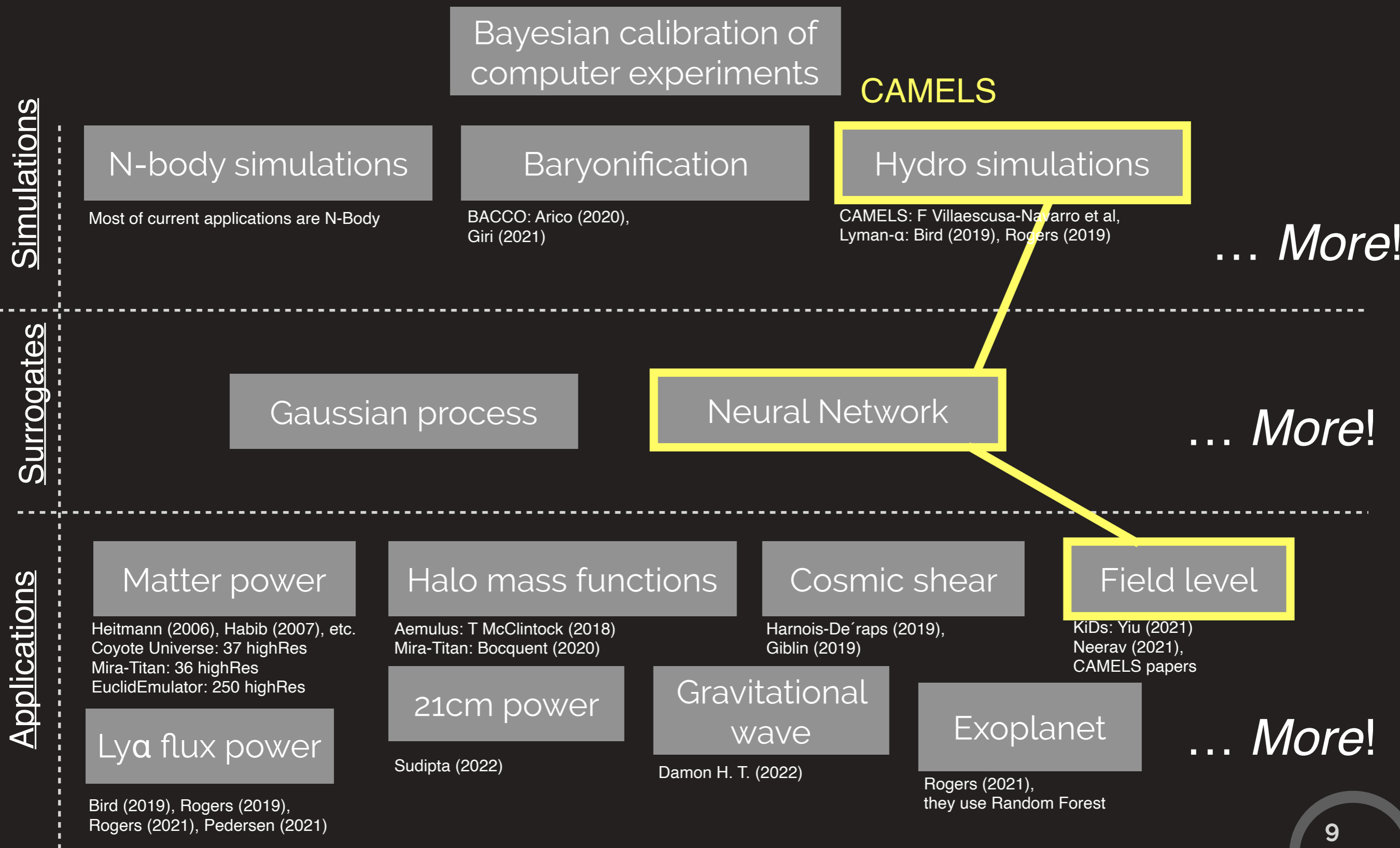
What's emulation?

Roadmap of building an emulator



What's emulation?

Roadmap of building an emulator



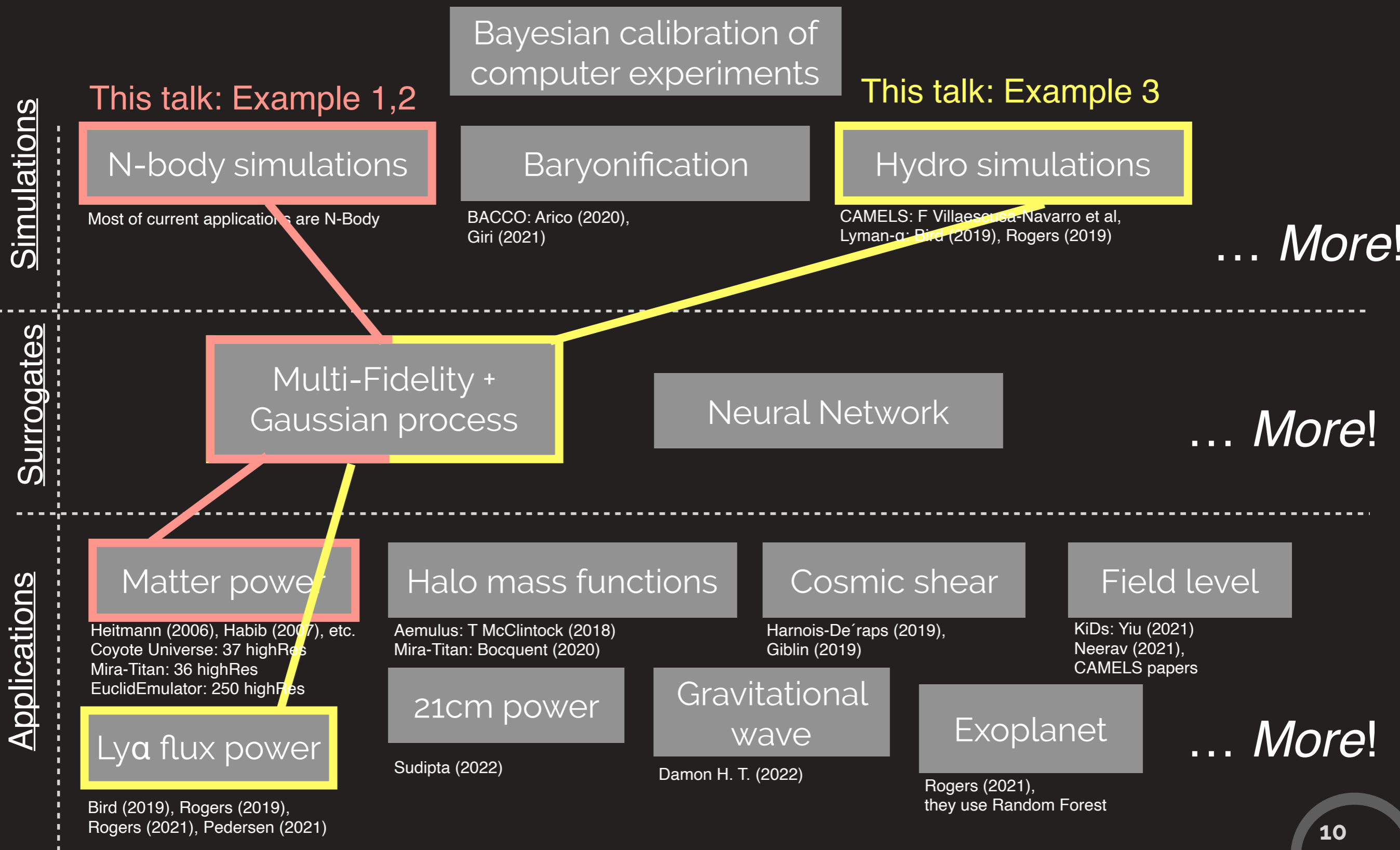
... More!

... More!

... More!

What's emulation?

Roadmap of building an emulator



What's multi-fidelity?

An analogy

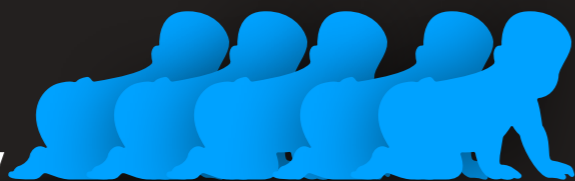


Many
Low-fidelity
simulations

+



A few
High-fidelity
simulations



Many
Grad Student Researchers

+



A few
Professors

= efficiency + accuracy

What's multi-fidelity?

Statistical modelling - regression view

- KO method (AR1): linear autoregressive GP

$$f_{\text{HF}}(x) = \rho f_{\text{LF}}(x) + \delta(x).$$

Scale, a value ρ $f_{\text{LF}}(x)$ Low-fidelity output, a GP $\delta(x)$ Bias function, a GP

- Nonlinear Autoregressive Gaussian Process (NARGP): An improved KO method using a deep GP

$$f_{\text{HF}}(x) = \rho(x, f_{\text{LF}}(x)) + \delta(x).$$

Scale function, a GP

KO: Kennedy & O'Hagan (2000)

NARGP: Perdikaris et al. (2017)

Example 1: matter power spectrum

Experimental design

- Parameters: $(h, \Omega_0, \Omega_b, A_s, n_s)$

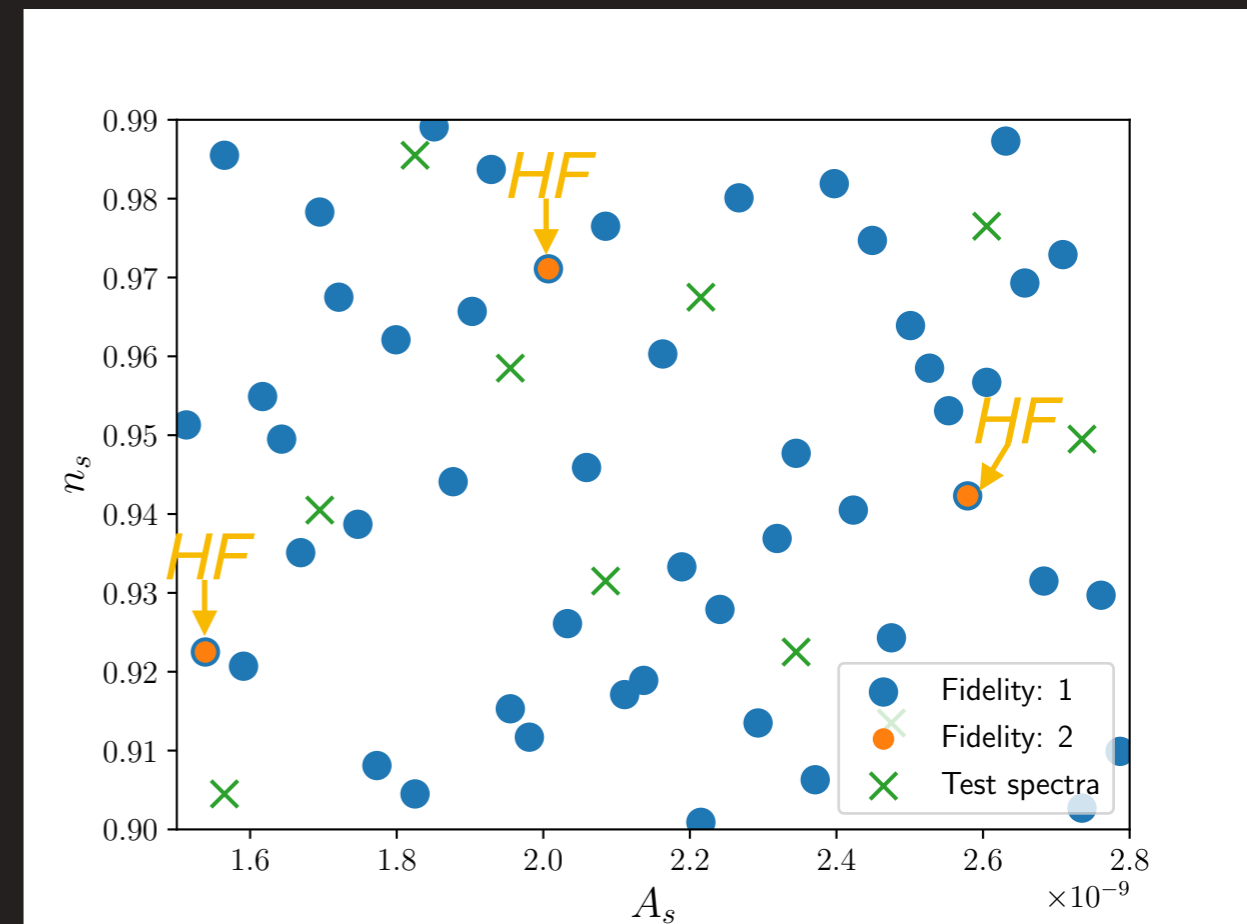
- Low-fidelity**: space-filling strategy (Latin hypercube)

- $128^3, 256 \text{ Mpc h}^{-1}$

- High-fidelity**: a subset of low-fidelity runs

- $512^3, 256 \text{ Mpc h}^{-1}$

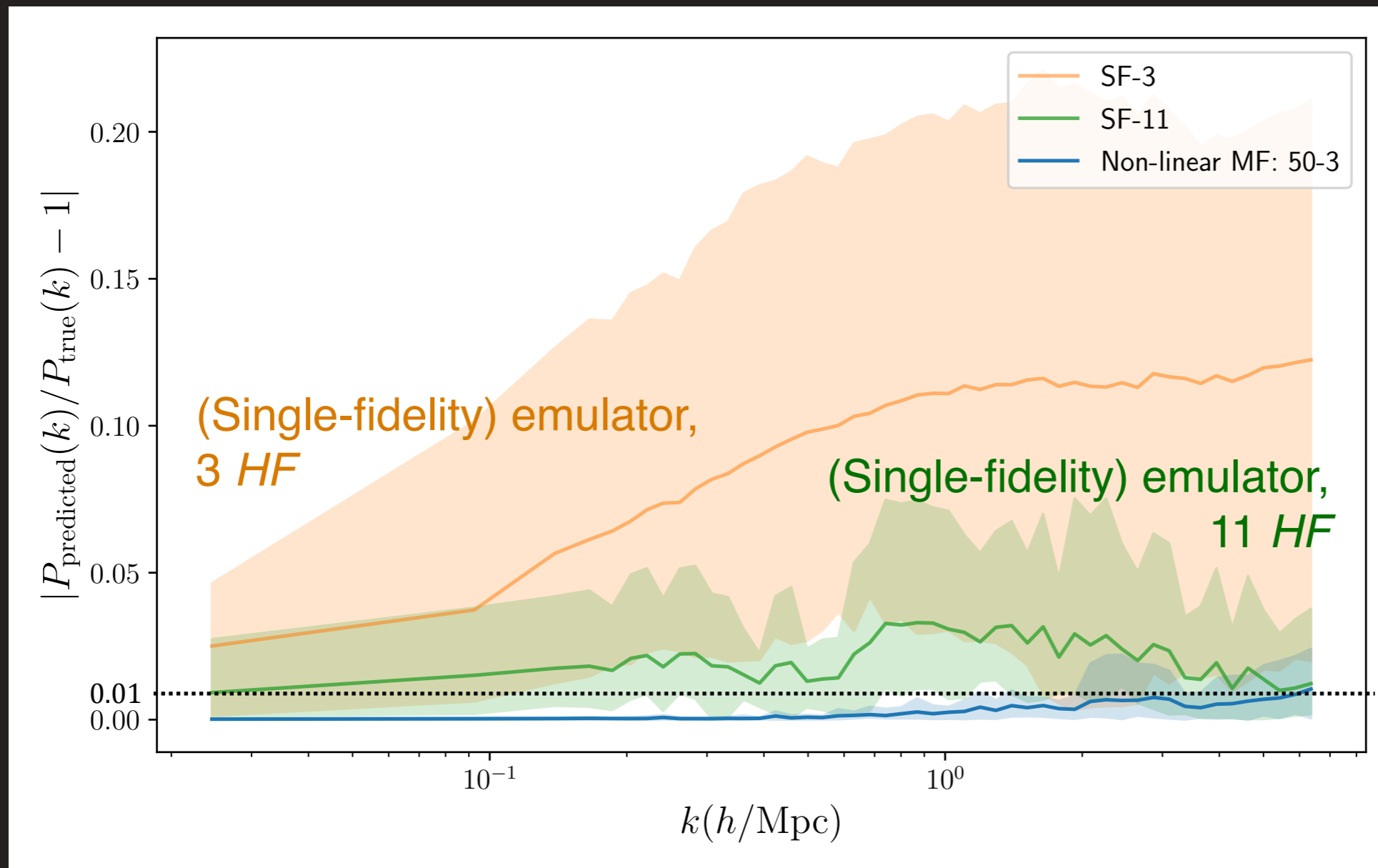
- HF** choices were optimized using **LF** simulations



Ho, Bird, Shelton (2022)

Example 1: matter power spectrum

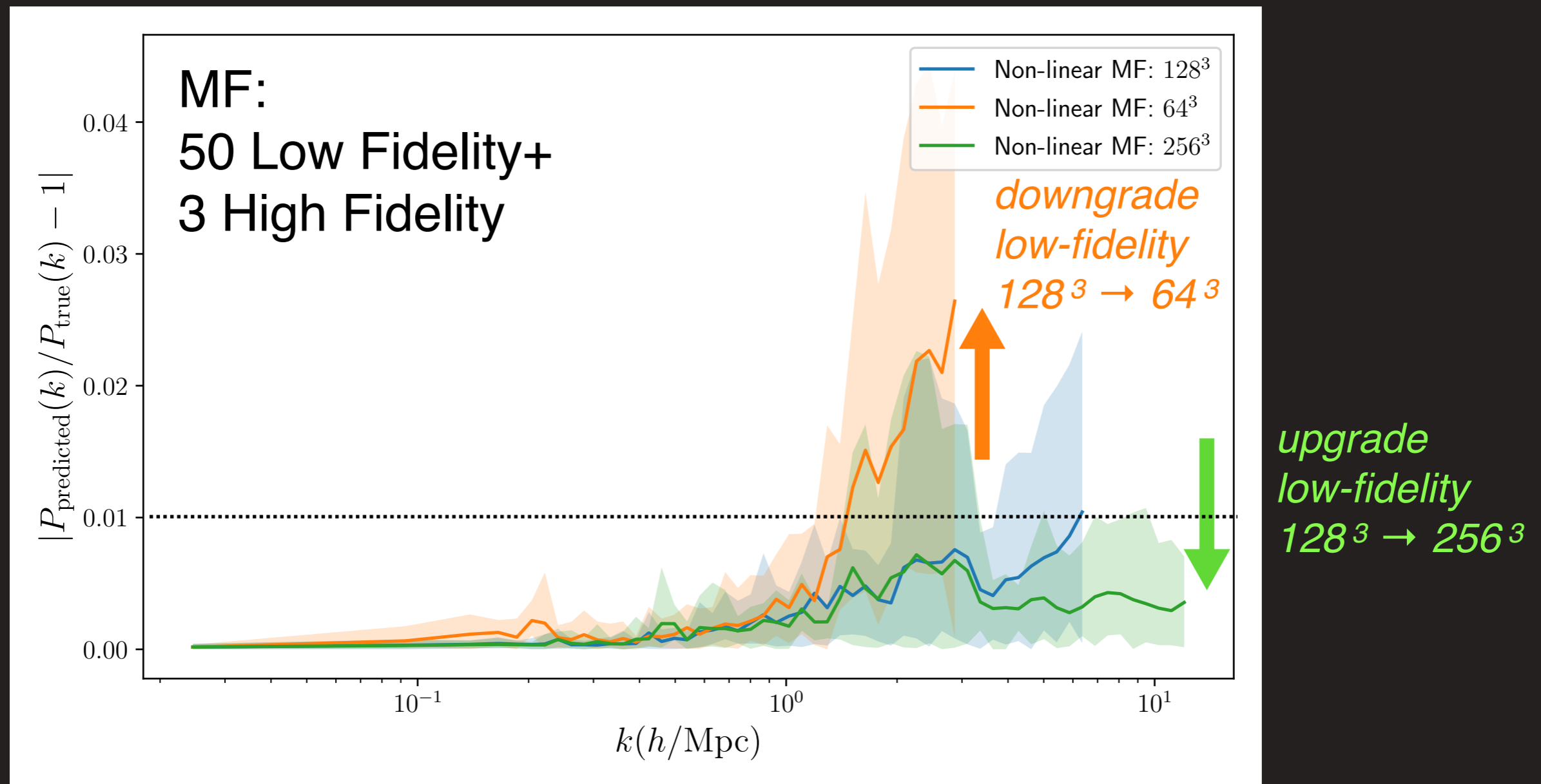
Emulation error ($z = 0$)



- The cost of 50 LF + 3 HF simulations is ~ 4 HF simulations.
- Still, the accuracy of MFEmulator is even better than using 11 HF.

Example 1: matter power spectrum

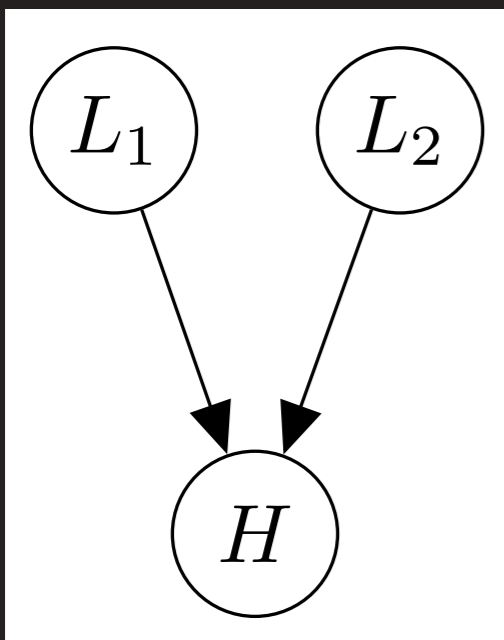
Accuracy increases with a better LF training set



- The quality of LF simulations affects the accuracy of MF emulation
- Small scales emulation can be improved with a better quality of LF simulation suite. → *Question: Can we use small box LF to improve emulation?*

Example 2: matter power spectrum

Extending to using **boxsize** as a fidelity



- L_1 : 128^3 , 256 Mpc/h
- L_2 : 128^3 , 100 Mpc/h
- H : 512^3 , 256 Mpc/h

- Number of particles is not the only fidelity variable, **boxsize** is also a fidelity variable
- A smaller boxsize, **better** resolution at **small scales**
- We can combine both **large box (L_1)** and **small box (L_2)** information through a graphical model construction.
- A graphical GP (Ji et al., 2021) allows us to do so.

Deep Graphical Multi-fidelity GP (dGMGP)

$$f_{\text{HF}}(x) = \rho(\{f_{\text{LF},1}, f_{\text{LF},2}\} \cup x) + \delta(x)$$

$$K([x, f_{\text{LF}}], [x', f'_{\text{LF}}]) = K_{\text{SE}}(x, x') [K_{\text{LIN}}(f_{\text{LF}}, f'_{\text{LF}}) + K_{\text{SE}}(f_{\text{LF}}, f'_{\text{LF}})] + K_{\text{SE}}(x, x')$$

K_{SE} : Squared-exponential kernel, guarantees smooth functions

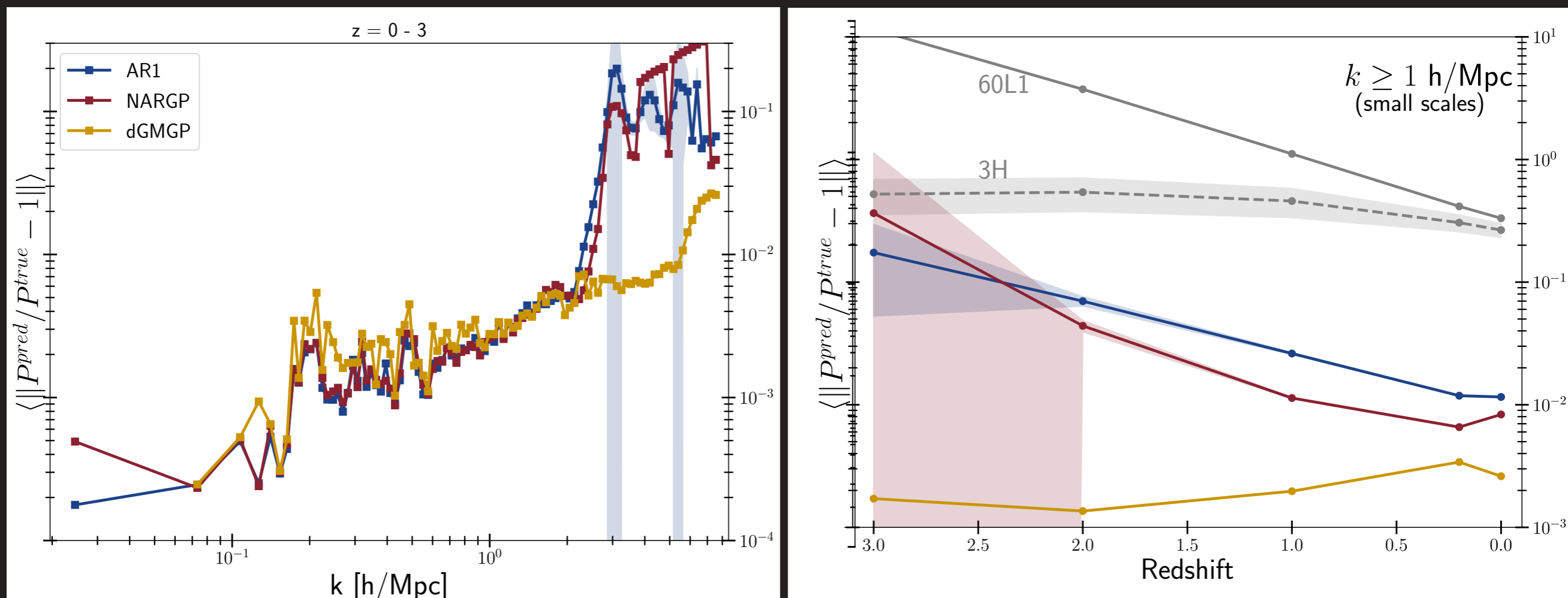
K_{LIN} : Linear kernel, doing Bayesian linear regression

GMGP: Ji (2021)

A graphical multi-fidelity Gaussian process model, with application to emulation of expensive computer simulations

Example 2: matter power spectrum

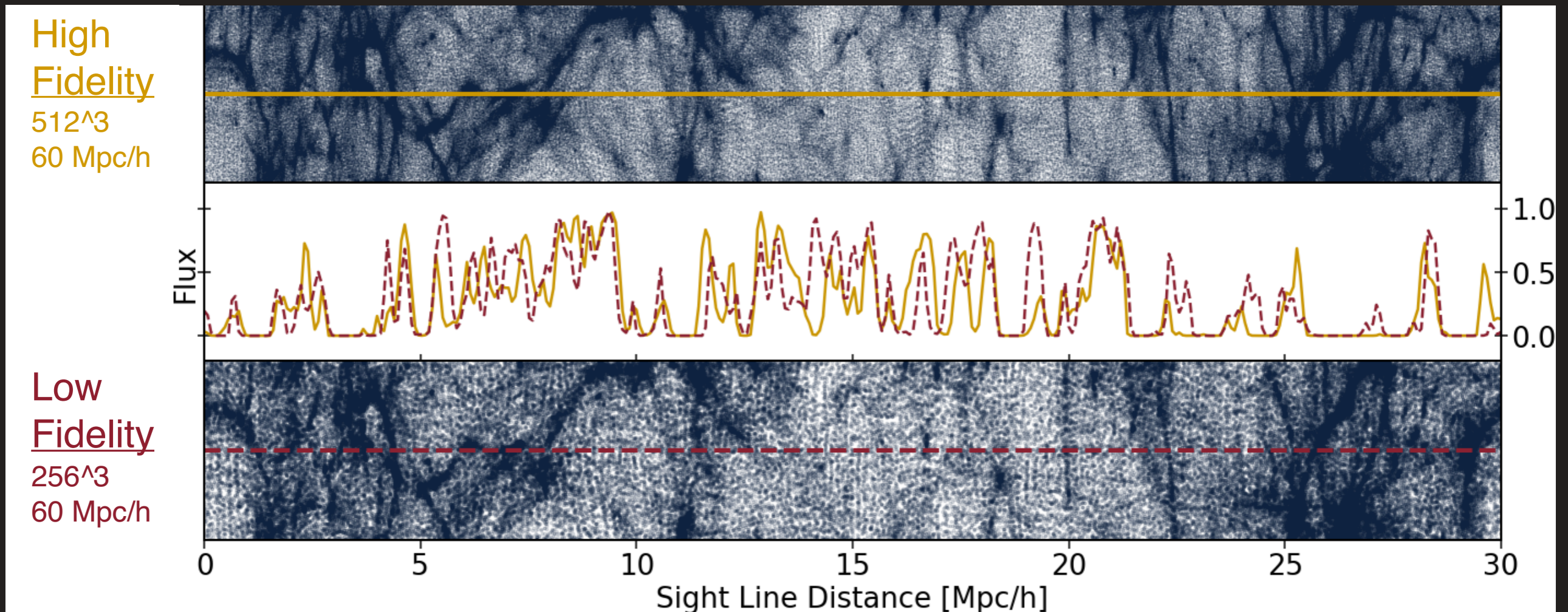
Extending to using **boxsize** as a fidelity



- GMGP uses smaller boxsize simulations to enhance the emulation accuracy at small scales.
- GMGP outperforms AR1 and NARGP at $z \geq 1$.
- It is possible to emulate HF using LF from various box sizes.

Example 3: Ly α flux power spectrum

Simulated spectra generation

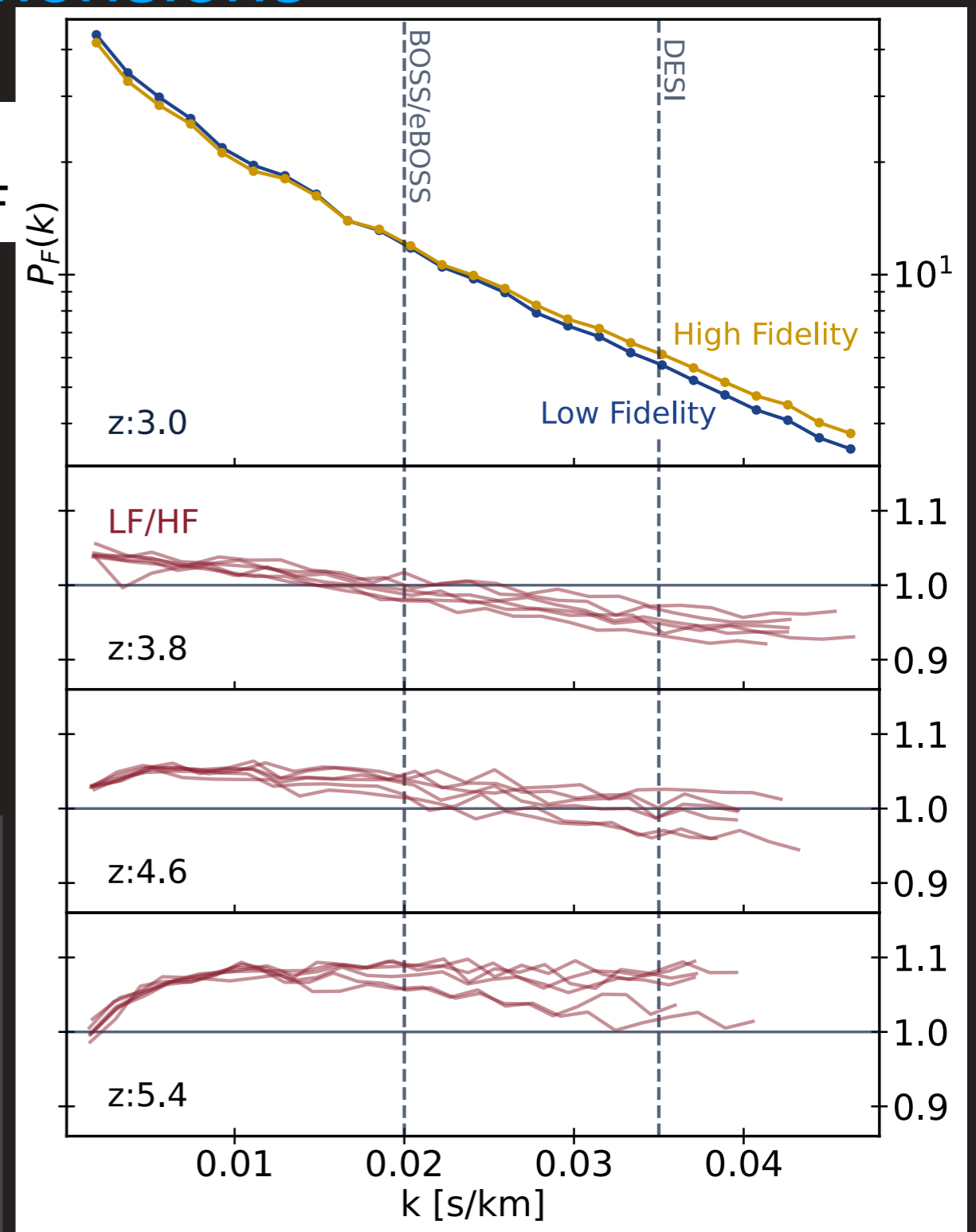
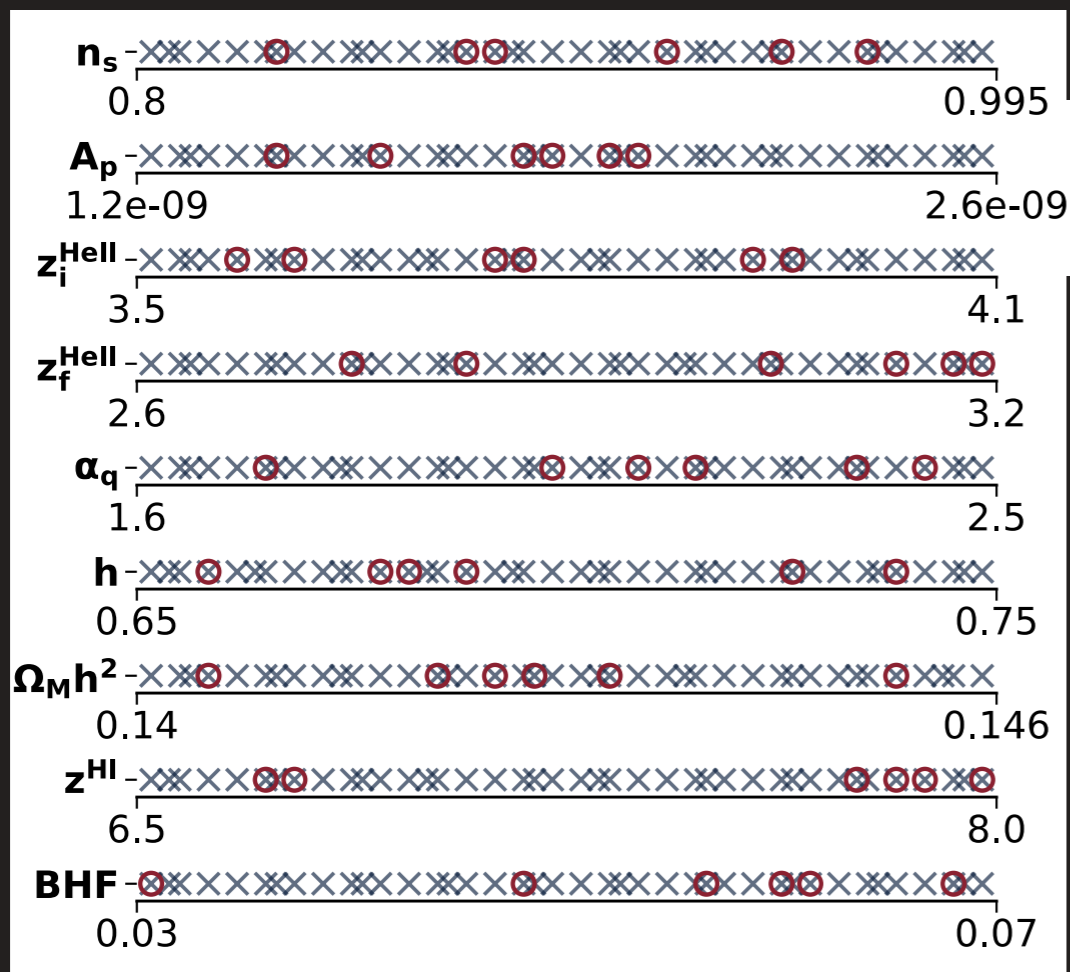


- Fake spectra: 32,000 (seeded) random skewers per snapshot using Bird (2017).
- Ly α flux power spectrum: Measure correlation between neutral hydrogen within a sightline

figure credit: Martin Fernandez

Example 3: Ly α flux power spectrum

Experimental design in 9 dimensions

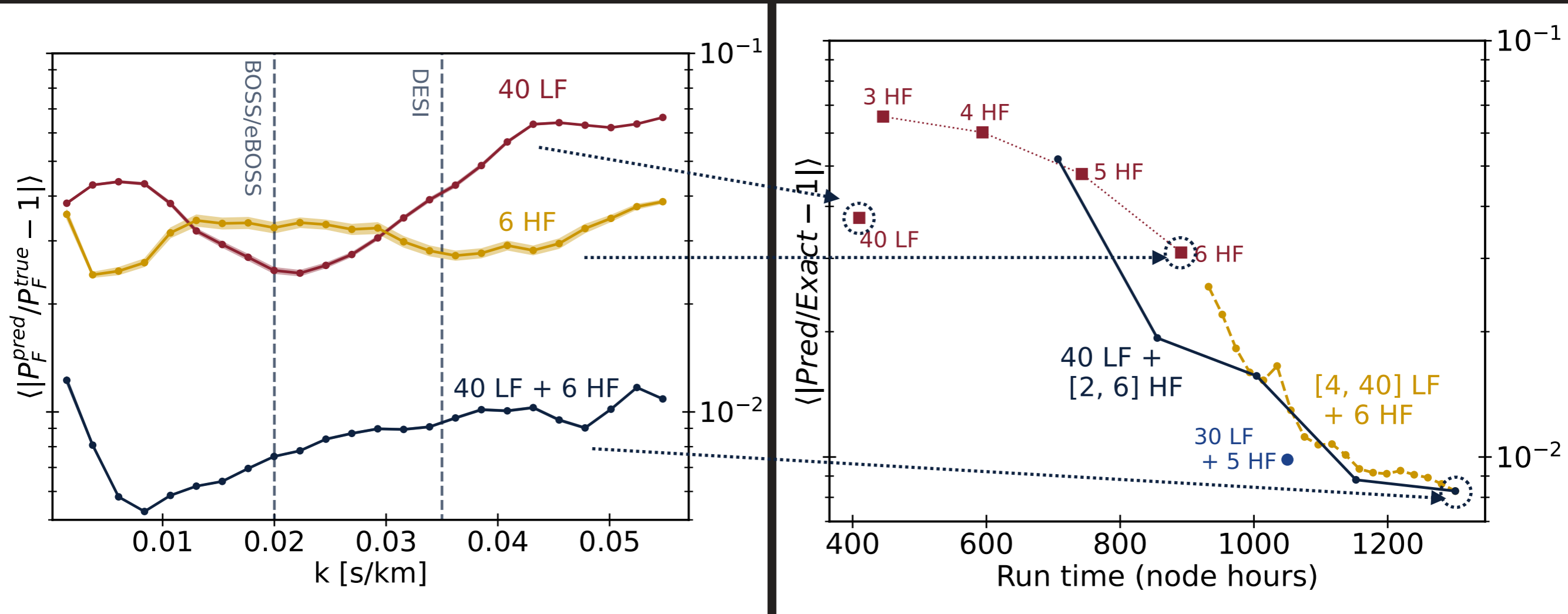


- 9 parameters ($z = 2 - 5.4$), including reionization parameters and black hole feedback
- The discrepancy between LF/HF appears across scales (k), varies with redshifts

figure credit: Martin Fernandez

Example 3: Ly α flux power spectrum

Emulation errors and computational cost



- MFEmulator with 40 LF + 6 HF has $\approx 1\%$ accuracy across all scales.
- Effectively increase the emulation accuracy by combining existing low and high-fidelity simulations.

figure credit: Martin Fernandez

Conclusion

- Save computation budget with multi-fidelity experimental designs.
- Multi-fidelity emulation can be directly applied to existing simulation suite.
- Cheaply increasing dynamic range of simulations.
- Example 1: matter power spectrum
- Example 2: matter power spectrum, emulating with different box sizes
- Example 3: Lya flux power spectrum
- Future applications: Halo mass function, cosmic shear power spectrum

[arXiv:2105.01081](https://arxiv.org/abs/2105.01081)

github.com/jibanCat/matter_multi_fidelity_emu

Papers for example 2 and 3 are expected to be submitted later this year.

We thanks Yi Ji (Duke, Stat) and Simon Mak (Duke, Stat) for kindly providing the GMGP code in Python.