

Multi-Fidelity Emulation for Matter Power Spectrum and Ly α Forest

... using Astrid simulation code

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NASA FINESST FI

1. Ho, Bird, Shelton (2022) [arXiv:2105.01081](https://arxiv.org/abs/2105.01081)
2. Fernandez, Ho, Bird (2022) [arXiv:2207.06445](https://arxiv.org/abs/2207.06445)
3. Ho, Bird, Fernandez, Shelton (in prep)



PHYSICS &
ASTRONOMY



Simeon Bird
(UCR Astro)



Martin A. Fernandez
(UCR Astro)



Christian Shelton
(UCR CS)

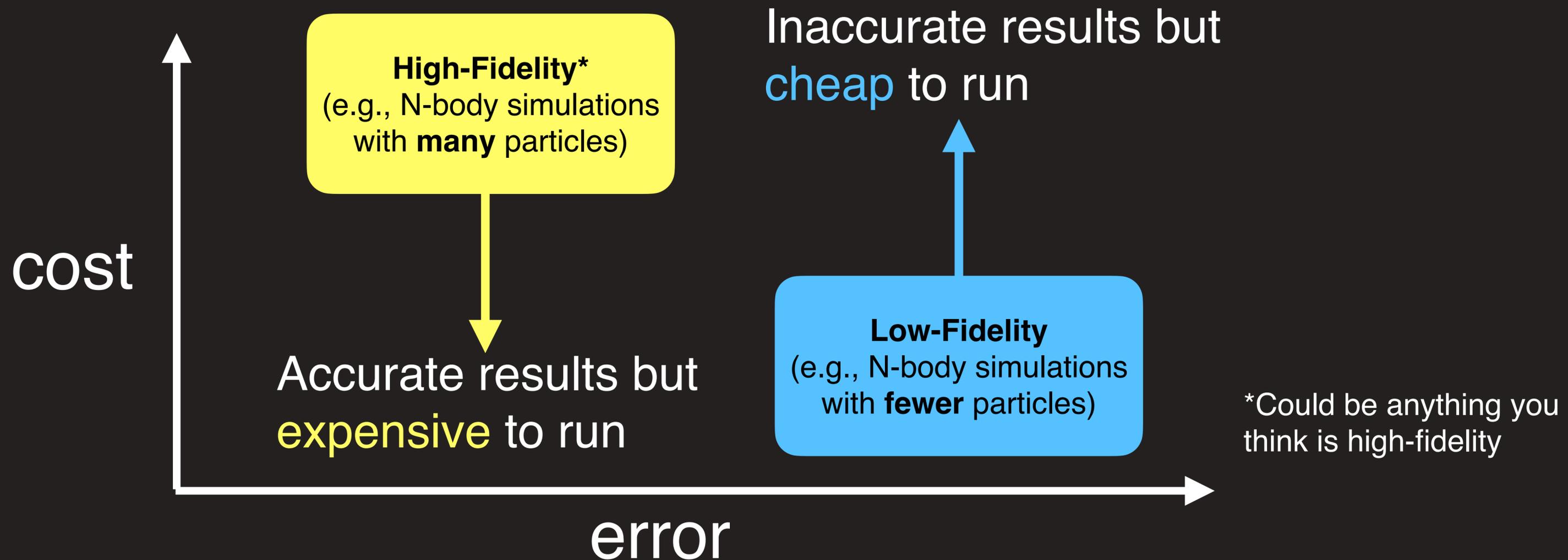


Outline

- What's multi-fidelity emulation?
- Example 1: Matter power spectrum using DM only simulations with different number of particles + box sizes
- Example 2: Lyman alpha 1D flux power using Astrid simulations with different number of particles

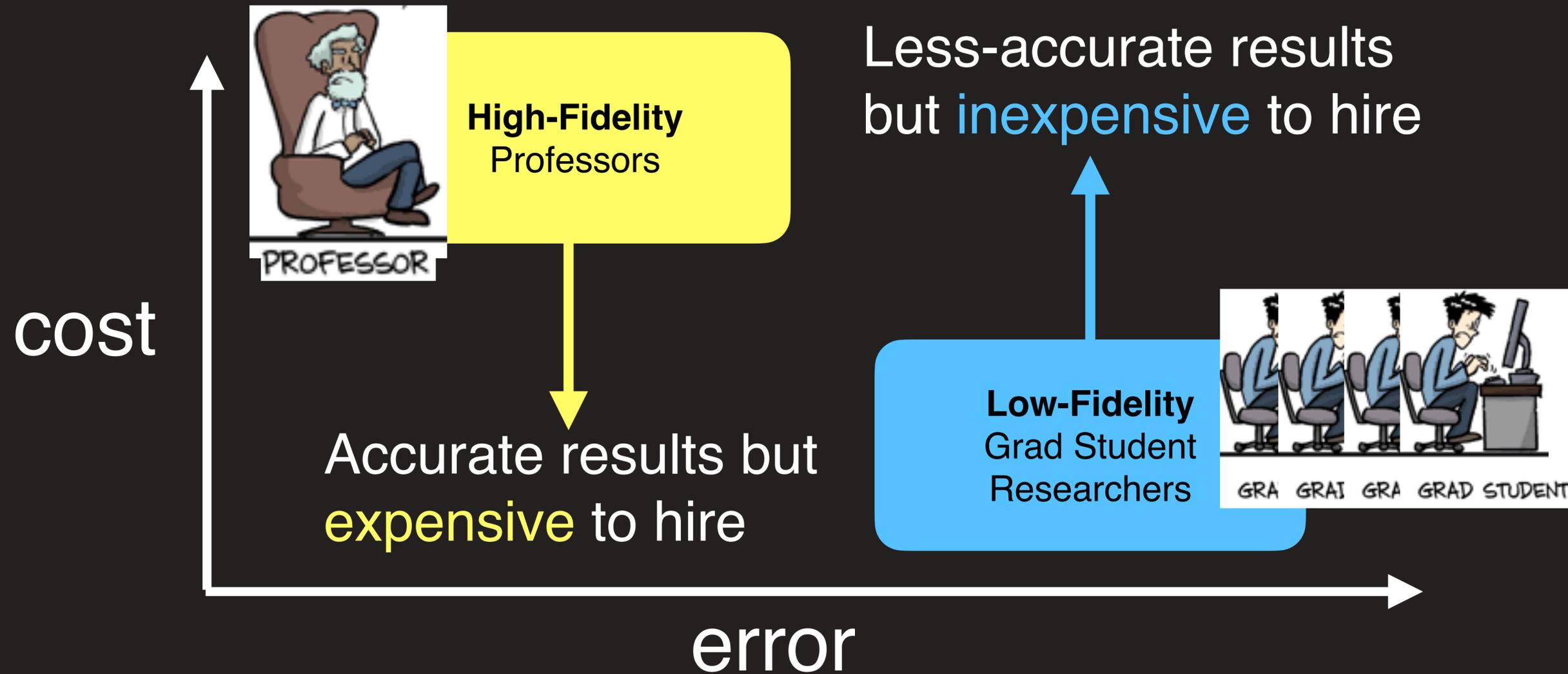
What's multi-fidelity emulation?

The trade-off between speed and accuracy



*Idea: Many LF + A few HF
= minimize the cost and maximize the accuracy.*

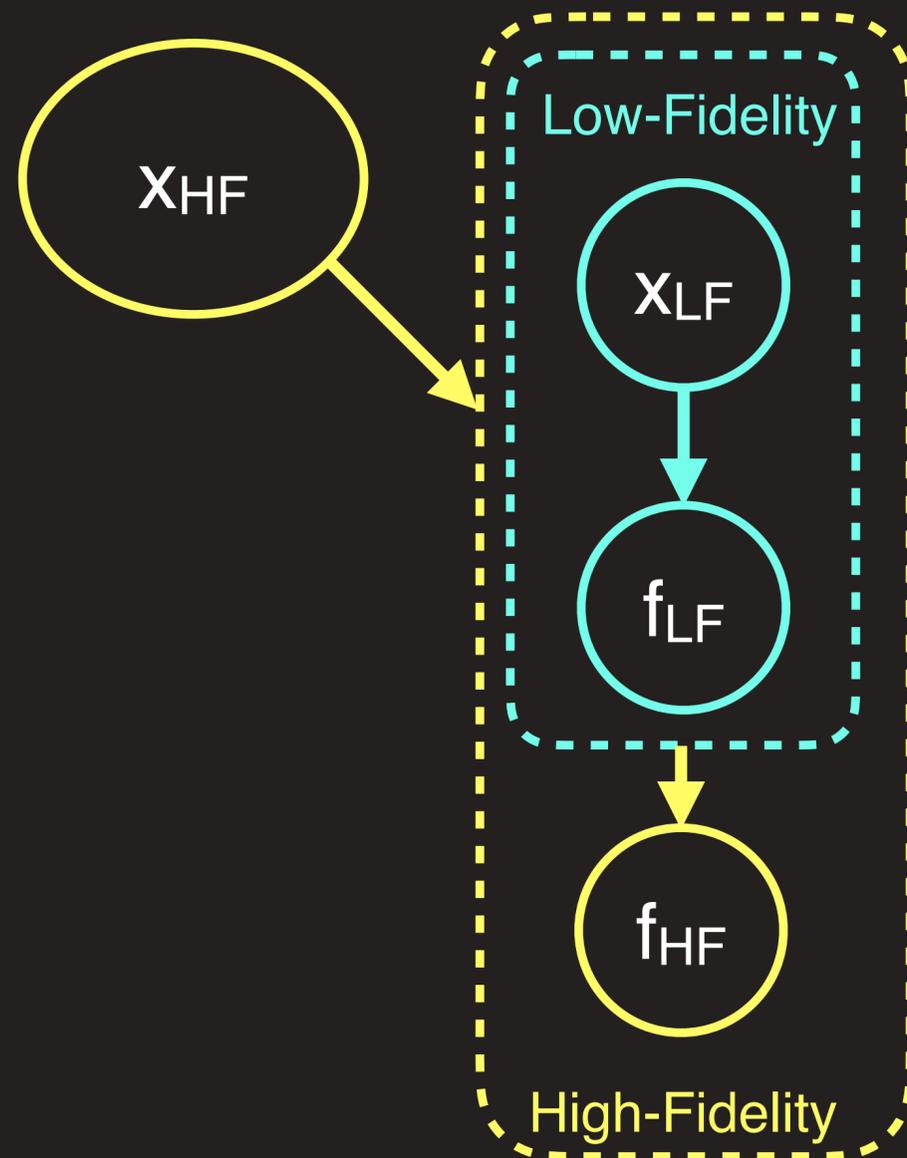
What's multi-fidelity emulation? An analogy: University's hiring



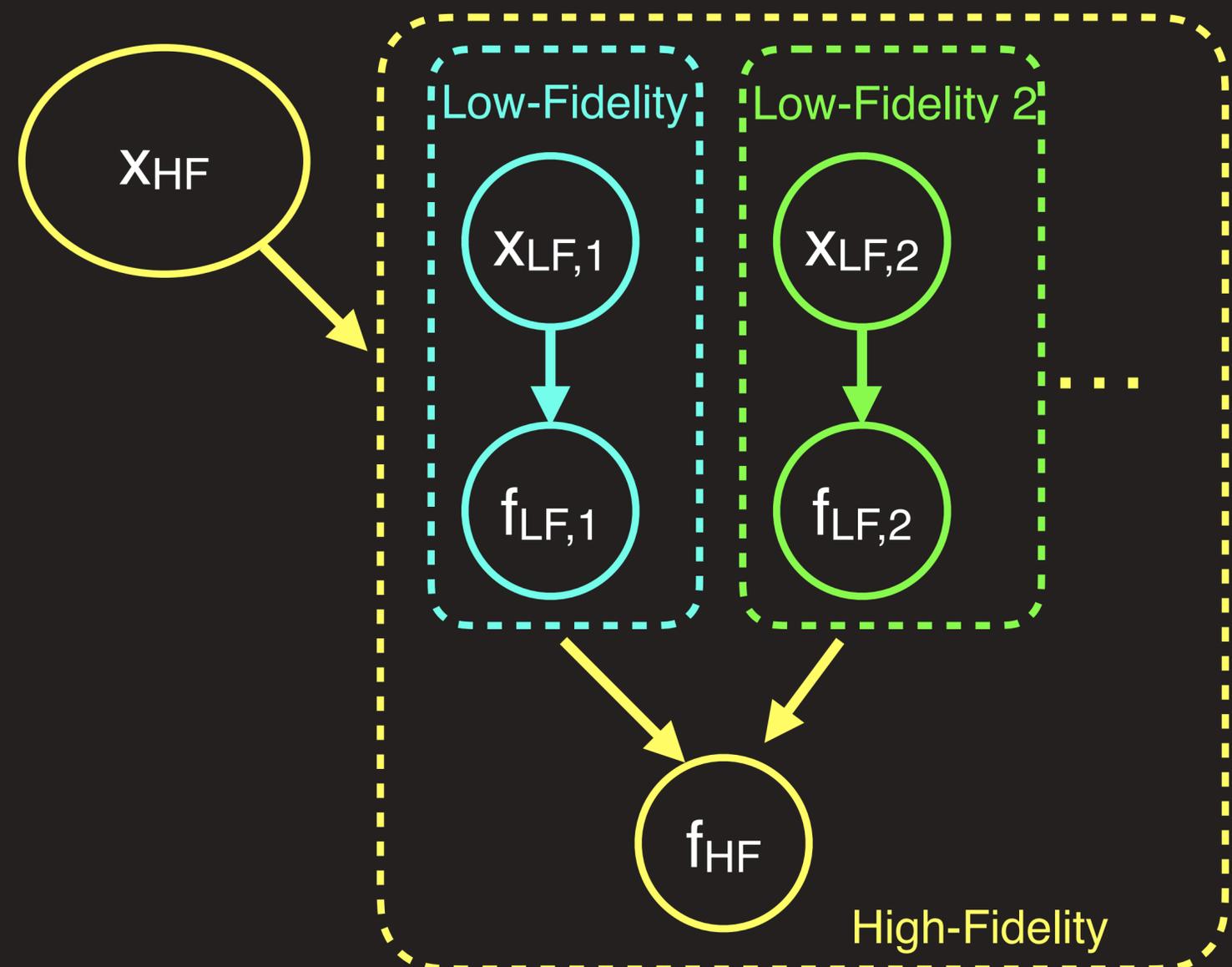
*Idea: Many Grad Students + A few Professors
= minimize the cost and maximize the accuracy.*

Multi-fidelity emulators: Transfer learn the information from low-fidelity

Kennedy & O'Hagan (2000)



Graphical model GP (2021)

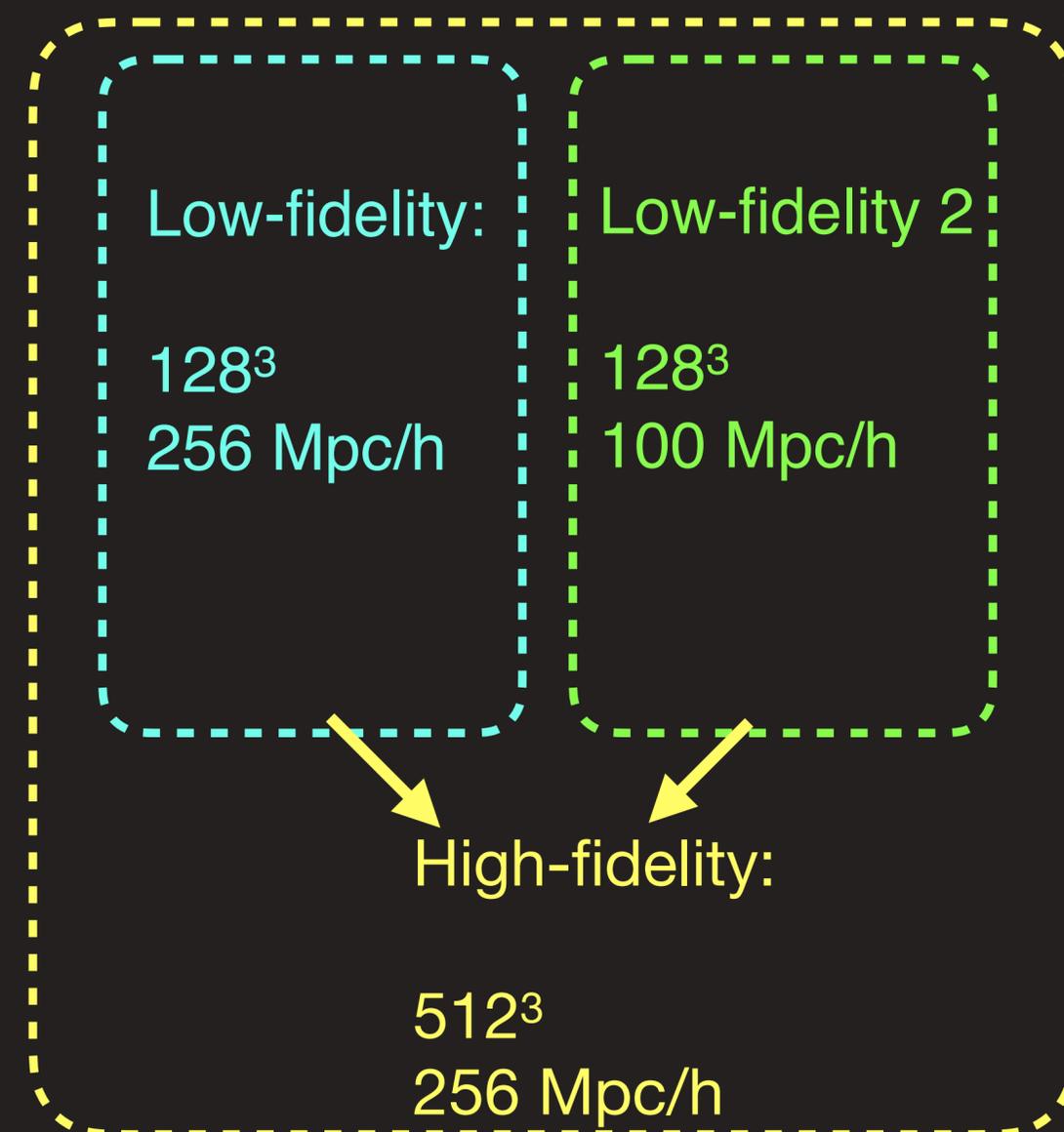
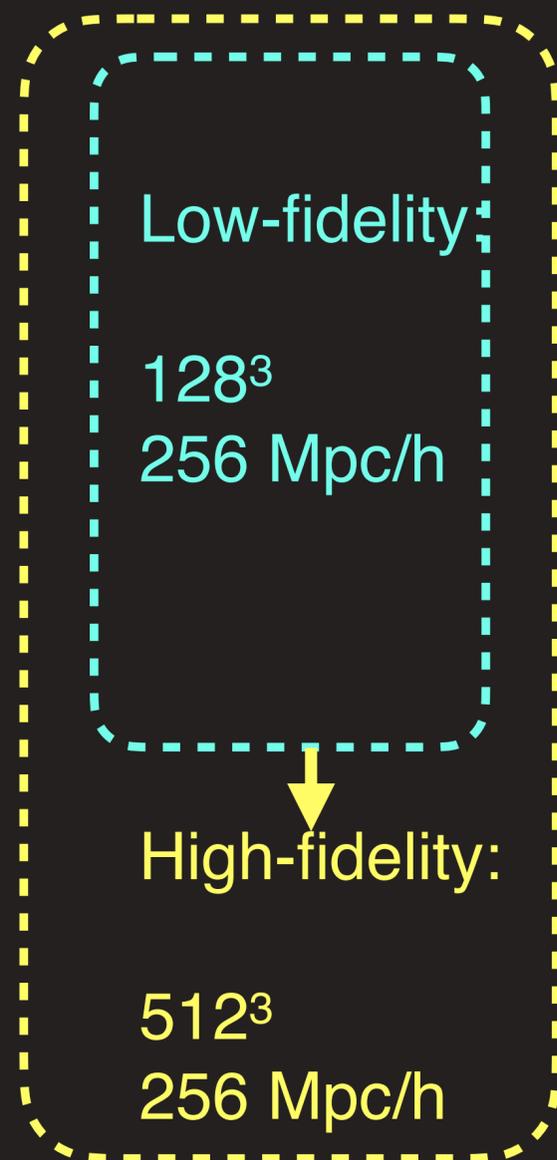


Deep GP: $f_{HF}(x) = \rho(x, f_{LF}(x)) + \delta(x)$.

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

Multi-fidelity emulators:

Transfer learn the the simulations from different resolutions + box sizes



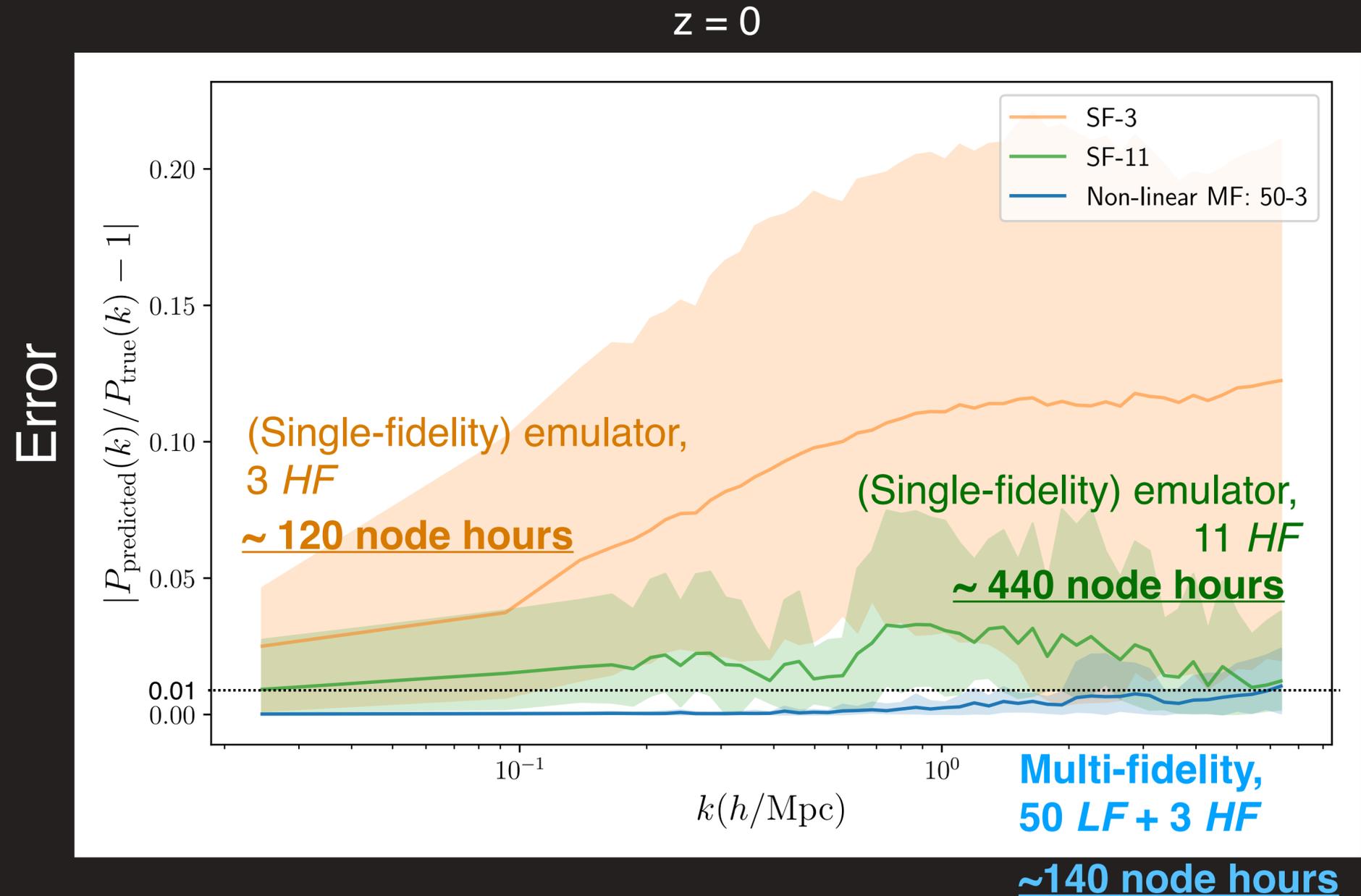
Deep GP: $f_{\text{HF}}(x) = \rho(x, f_{\text{LF}}(x)) + \delta(x)$.

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Example 1: matter power spectrum

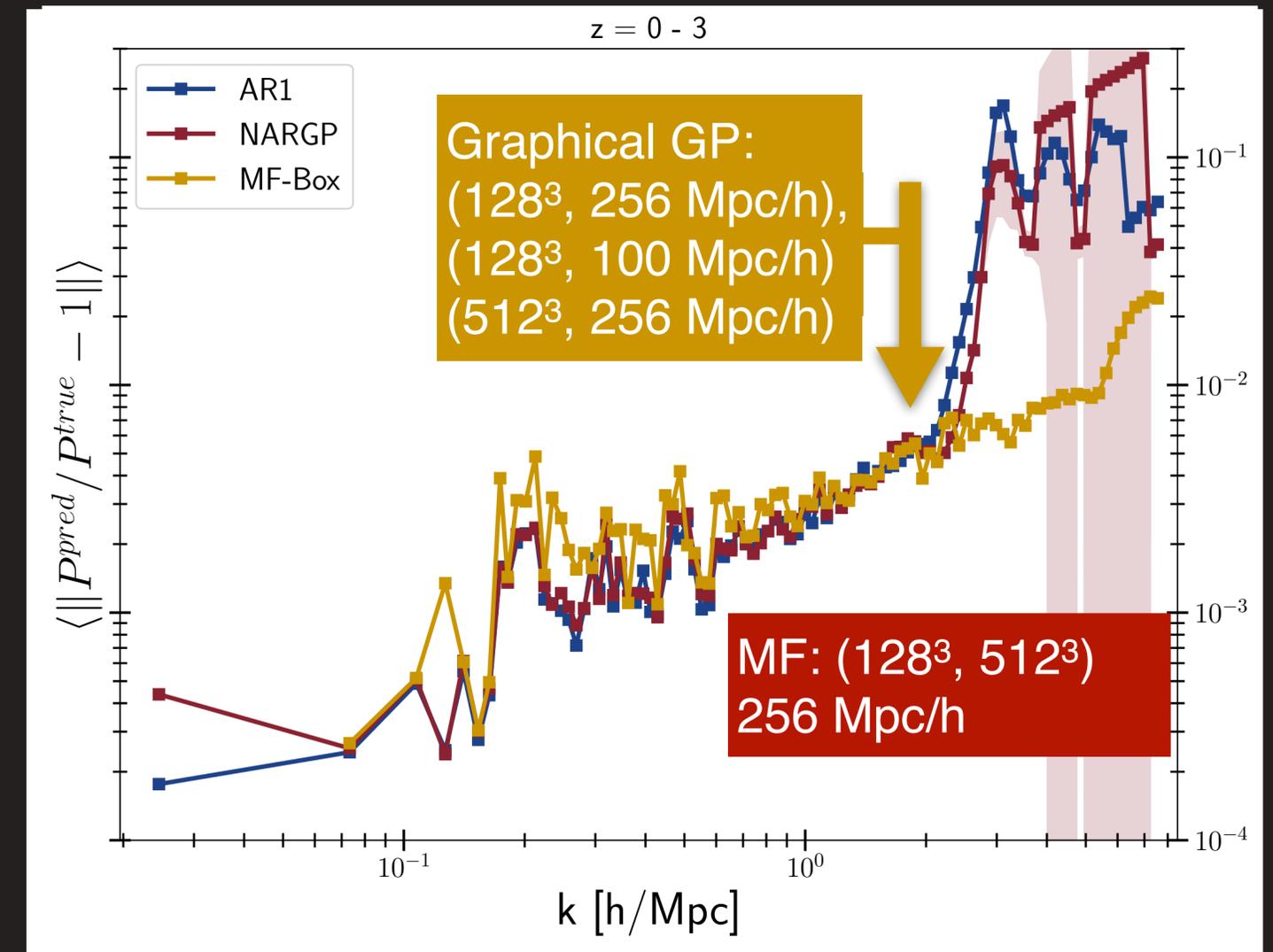
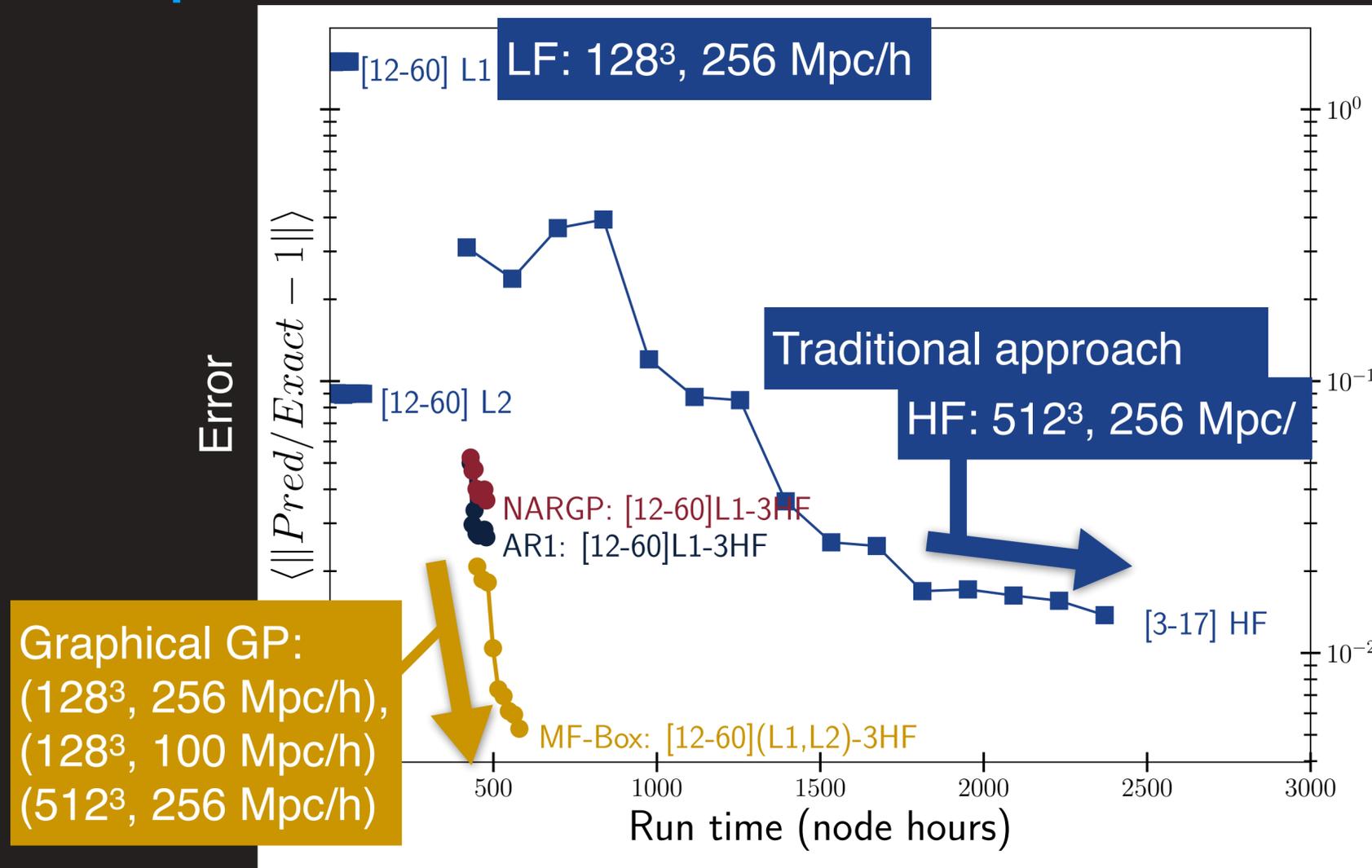
Experimental design using DM-only simulations

- Parameters: $(h, \Omega_0, \Omega_b, A_s, n_s)$
- 50 Low-fidelity**: space-filling strategy (Latin hypercube)
 - $128^3, 256 \text{ Mpc } h^{-1}$
- 3 High-fidelity**: a subset of low-fidelity runs
 - $512^3, 256 \text{ Mpc } h^{-1}$
- HF** choices were optimized using **LF** suite as a prior



Example 1: matter power spectrum

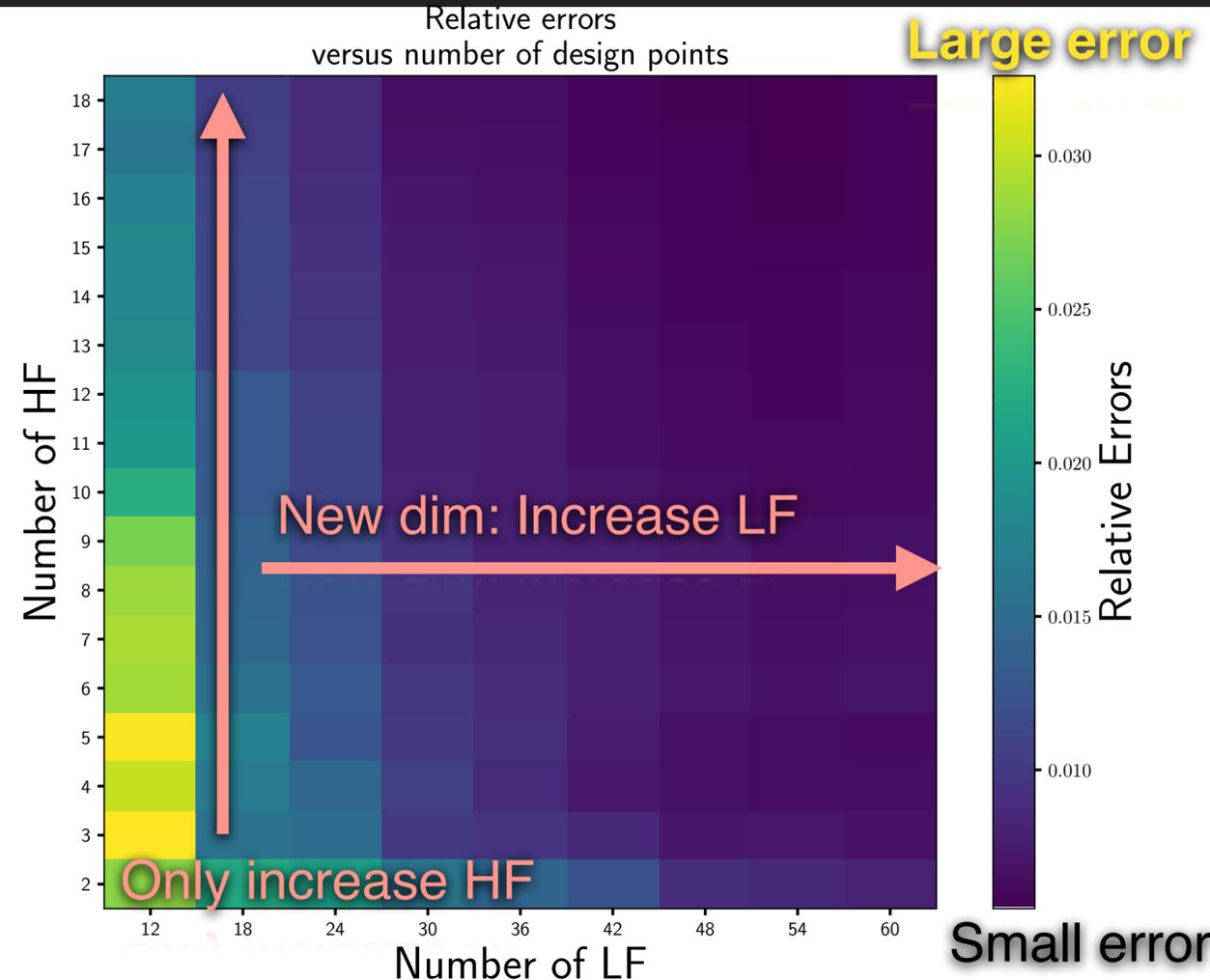
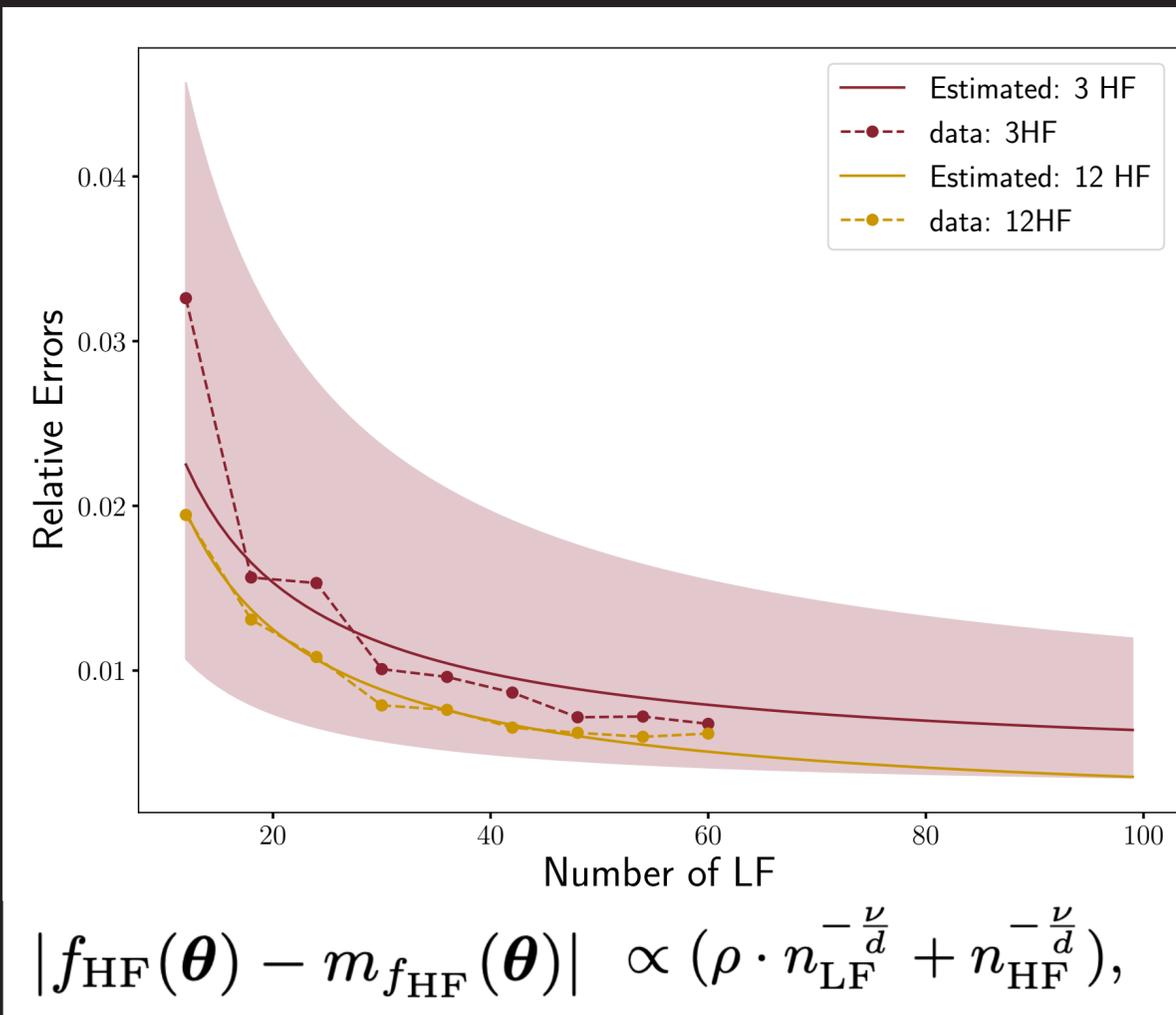
Graphical GP with simulations from different box sizes



- **MF** approach economically achieves sub-percent error, outperforming traditional single-fidelity emulator.
- **Graphical-GP** bridges the information from different box sizes.

Error analysis and budget estimation

- GP error roughly scales as a **power law** of the number of **training points**
- Each **multi-fidelity node** opens **a new dimension** to improve the emulator accuracy



- Suggested budget:

$$n_{\text{HF}} \propto \left(\frac{1}{C_{\text{HF}}} \right)^{\frac{d}{\nu+d}}$$

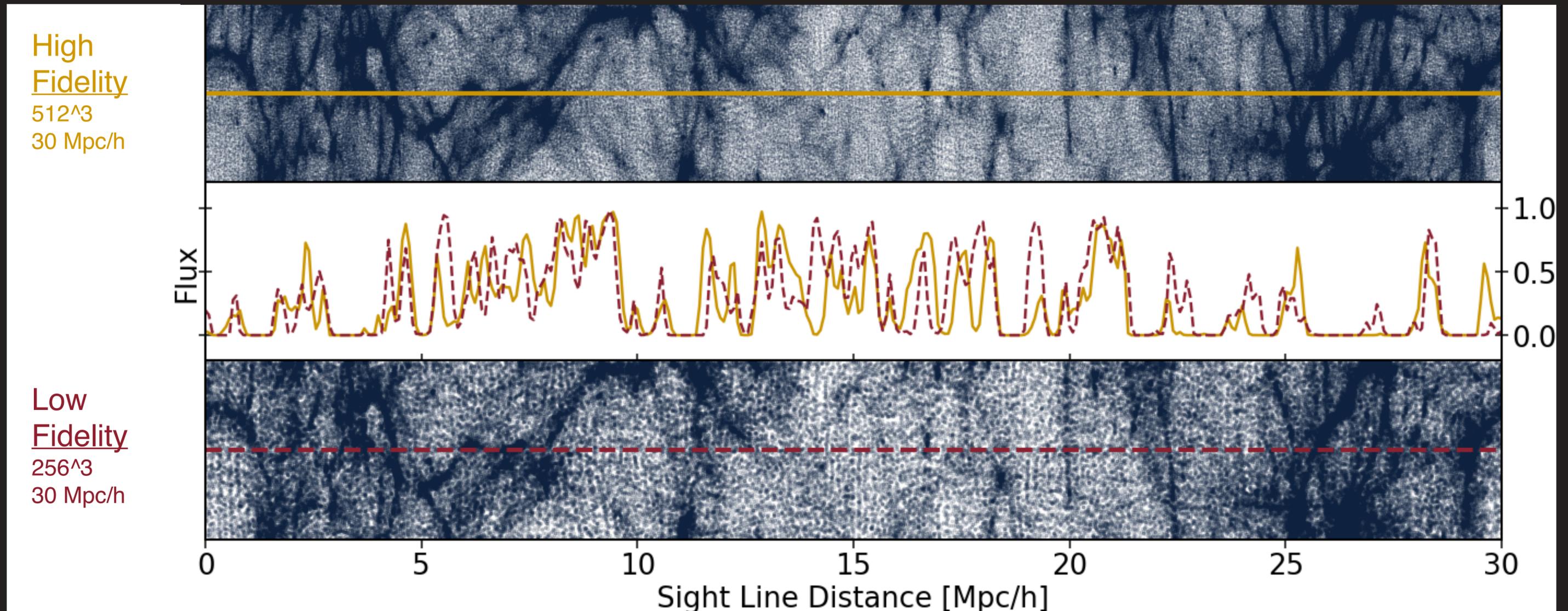
$$n_{\text{LF}} \propto \left(\frac{\rho}{C_{\text{LF}}} \right)^{\frac{d}{\nu+d}}$$

Based on: Ji (2021)

- n_{HF} : number of HF simulations
- C_{HF} : cost of a HF simulation
- ρ : correlation between LF and HF

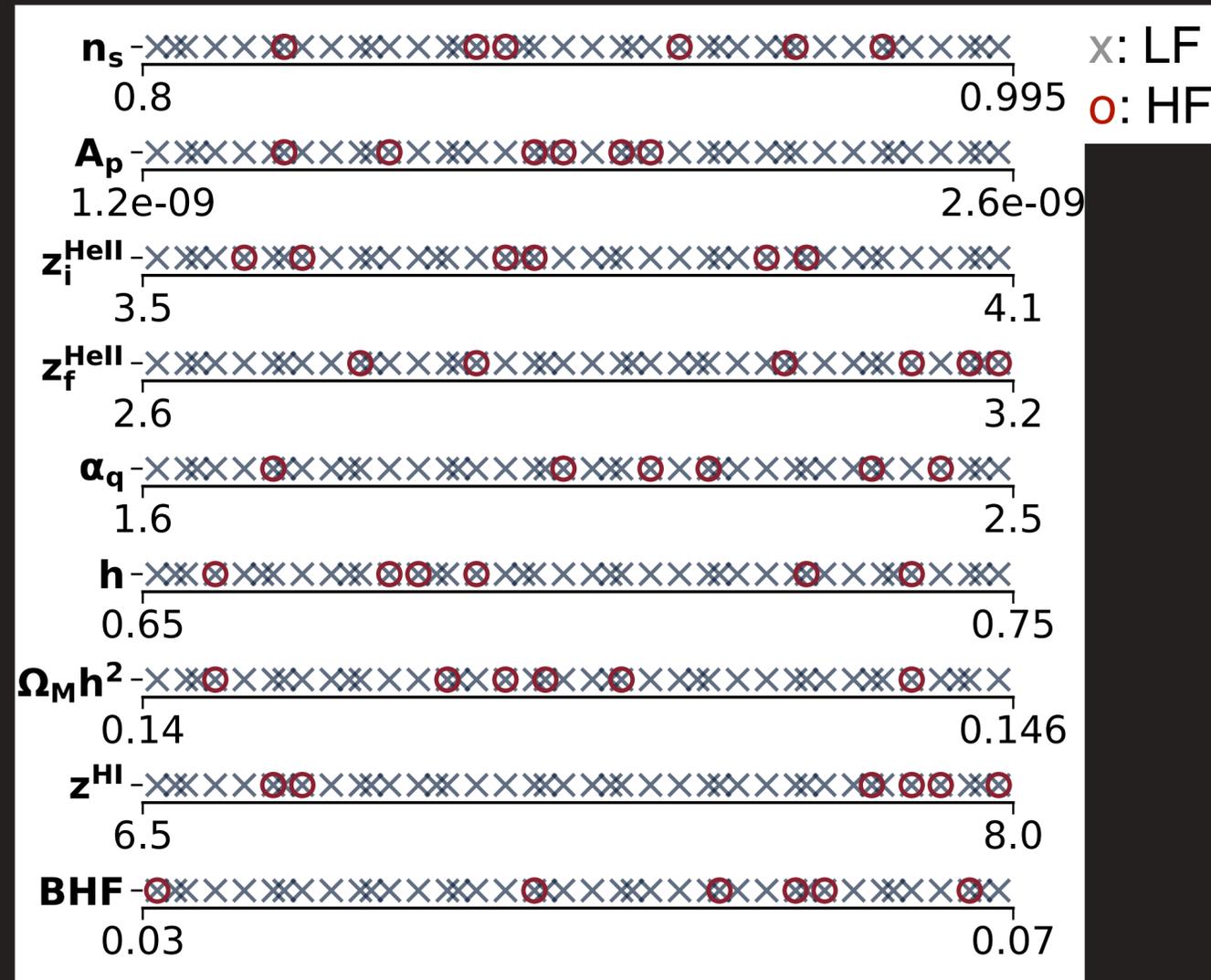
Example 2: Ly α flux power spectrum

Simulated Ly α forest using Astrid simulations (30 Mpc/h)

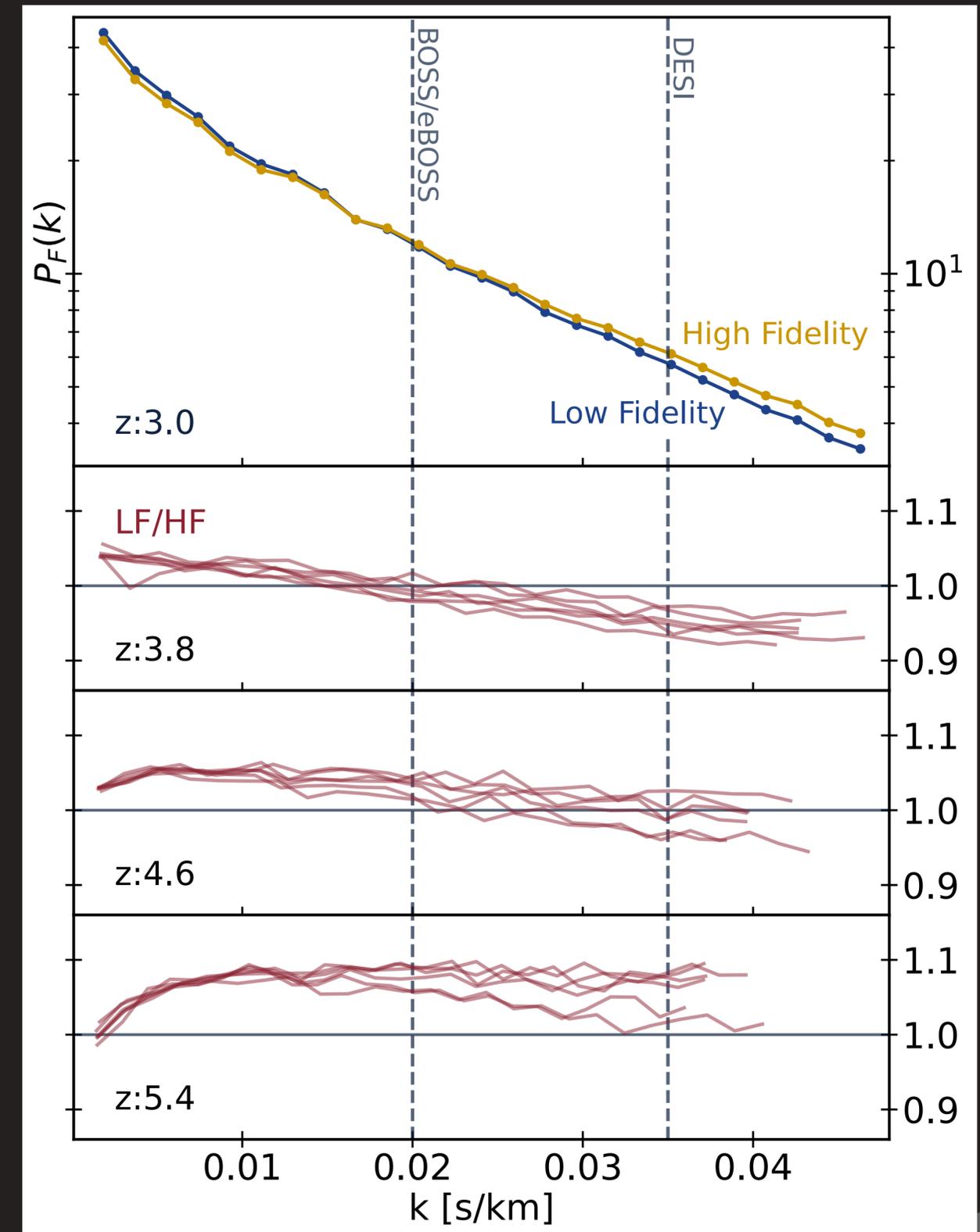


- 32,000 simulated spectra per snapshot
- **Ly α flux power spectrum**: Measure correlation between neutral hydrogen within a sightline

Example 2: Ly α flux power spectrum Experimental design in 9 dimensions

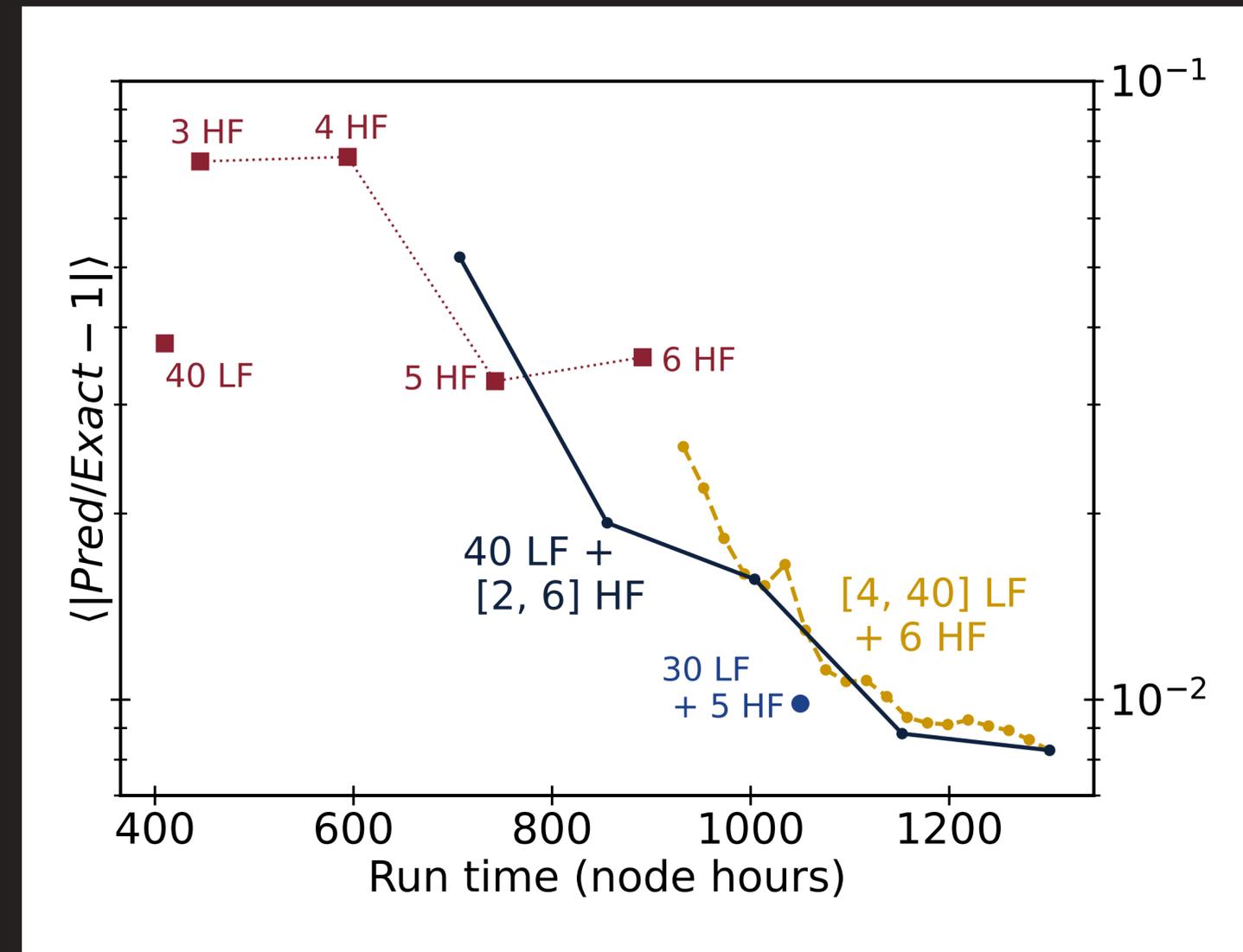
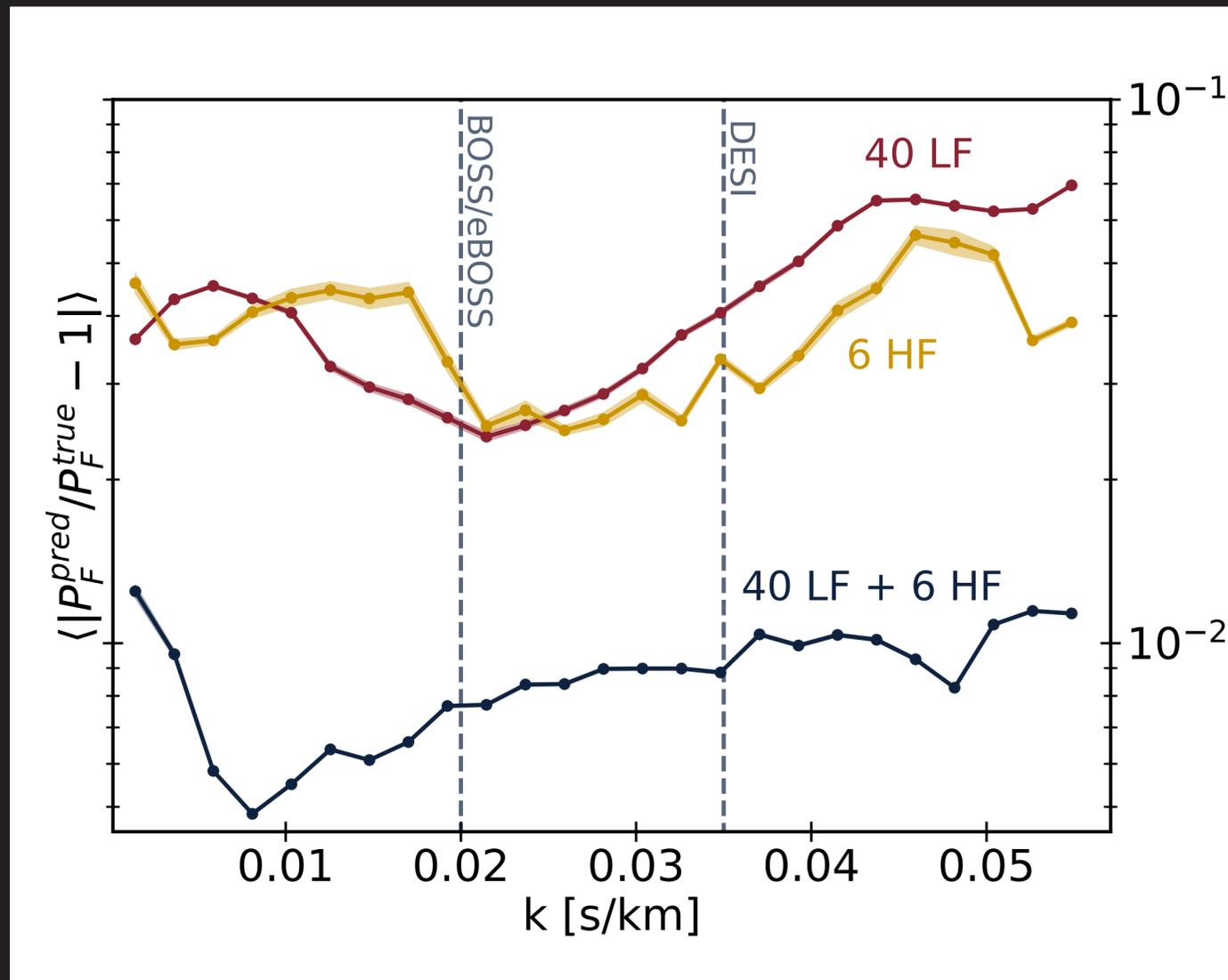


- 9 parameters ($z = 2 - 5.4$), including reionization parameters and black hole feedback
- Choice of HF optimized using LF suite as a prior



Example 2: Ly α flux power spectrum

Application to Ly α flux power



- MFE emulator with **40 LF + 6 HF** has $\approx 1\%$ accuracy.

Conclusion

- *Multi-fidelity emulation* economically uses simulations from different qualities
- Example 1: First application of MFEmulator to cosmology (DM only)
- Example 2: Application to Ly α forest (Astrid) → currently running large-volume production runs
- Possibilities in applying to CAMELS
 - Help fill the parameter space of SB-28 using many more low-fidelity simulations
 - Bridge the information from different box sizes at the emulation level

[arXiv:2105.01081](https://arxiv.org/abs/2105.01081) | github.com/jibanCat/matter_multi_fidelity_emu

[arXiv:2207.06445](https://arxiv.org/abs/2207.06445) | github.com/mafern/MFEmulatorLyaData

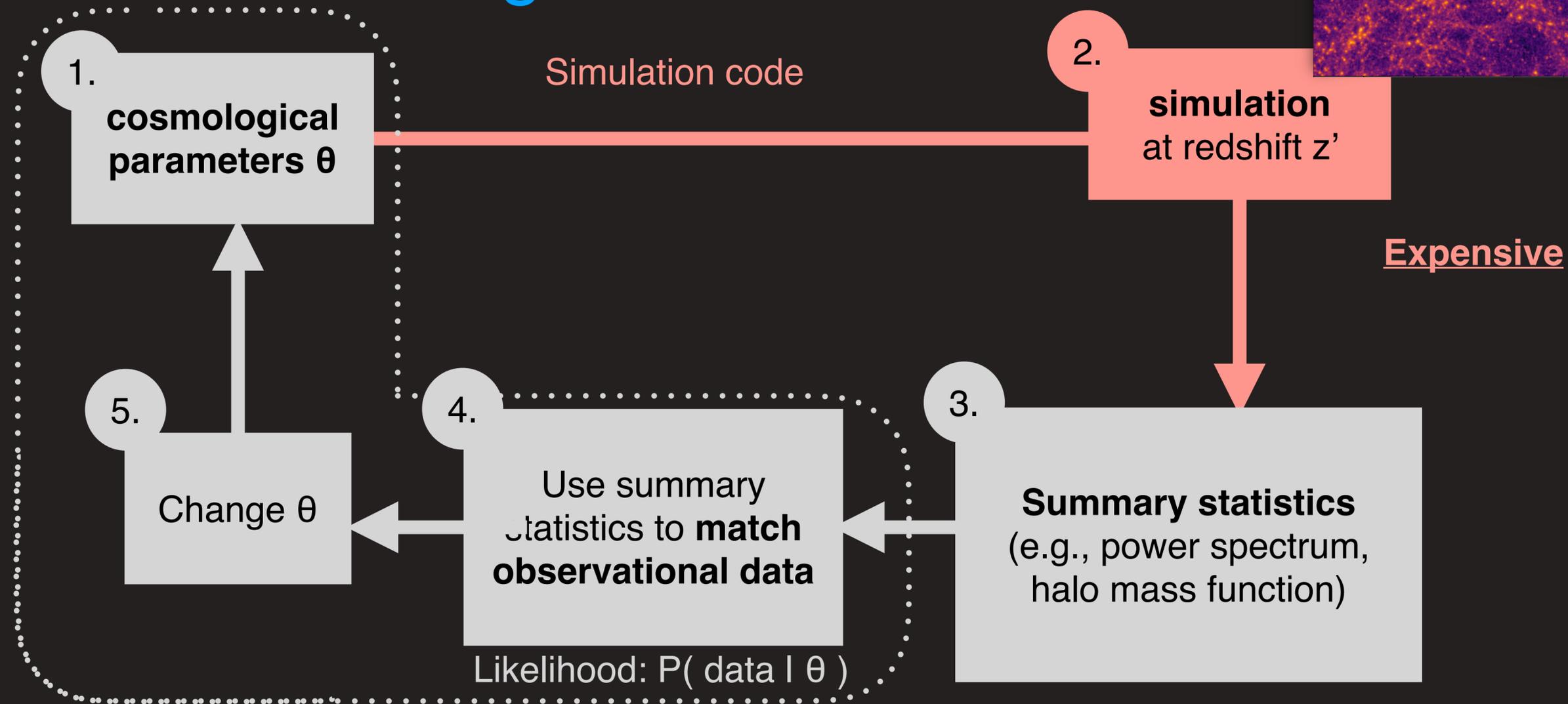
Paper for Graphical GP is expected to be submitted later this year.

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

Backup slides

What's emulation?

Bayesian inference using simulations



- Slide 4: figures b big as th also em simulation do this it simulation

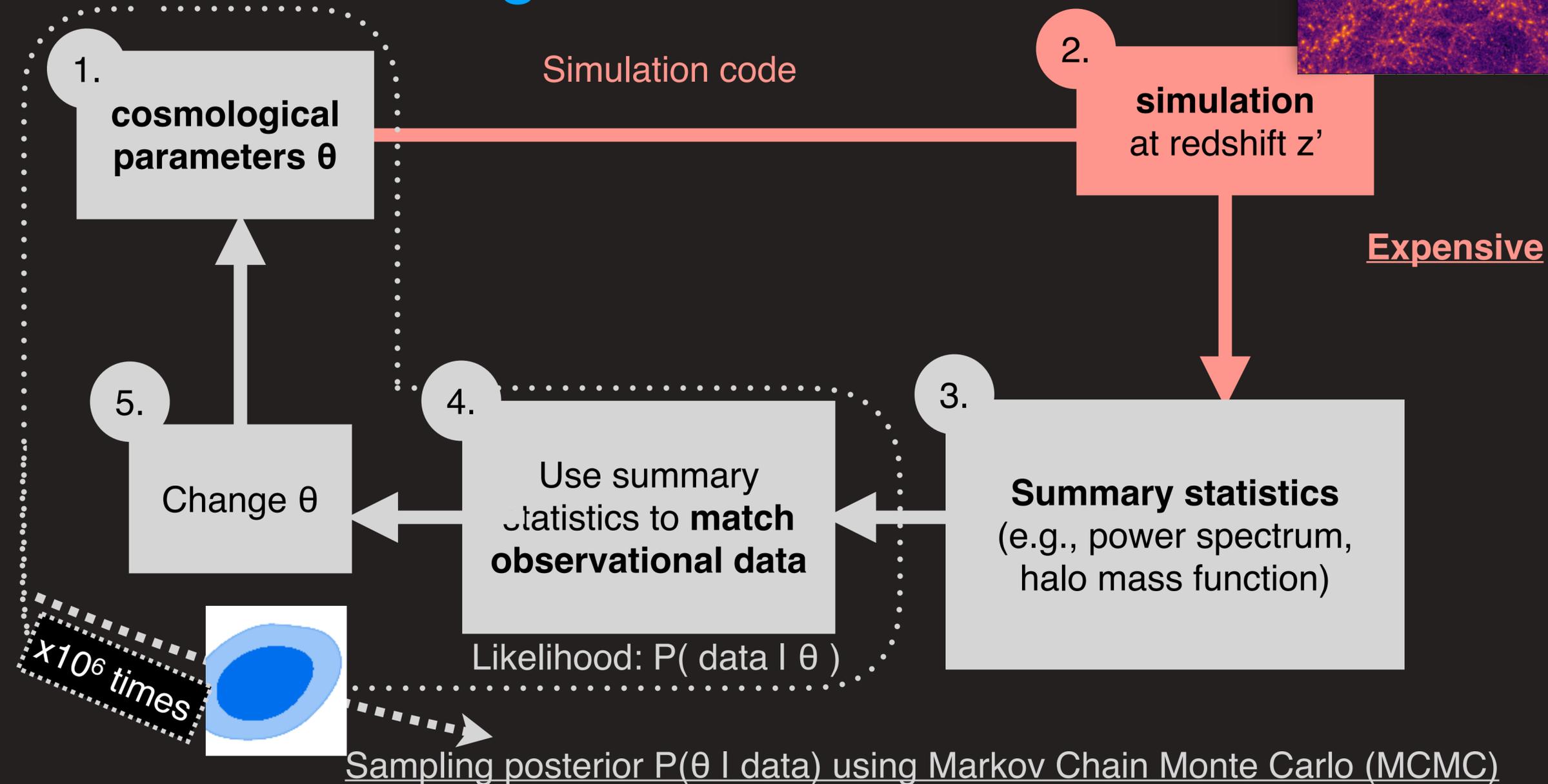
- An analo

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image credit: wiki, cobaya

What's emulation?

Bayesian inference using simulations



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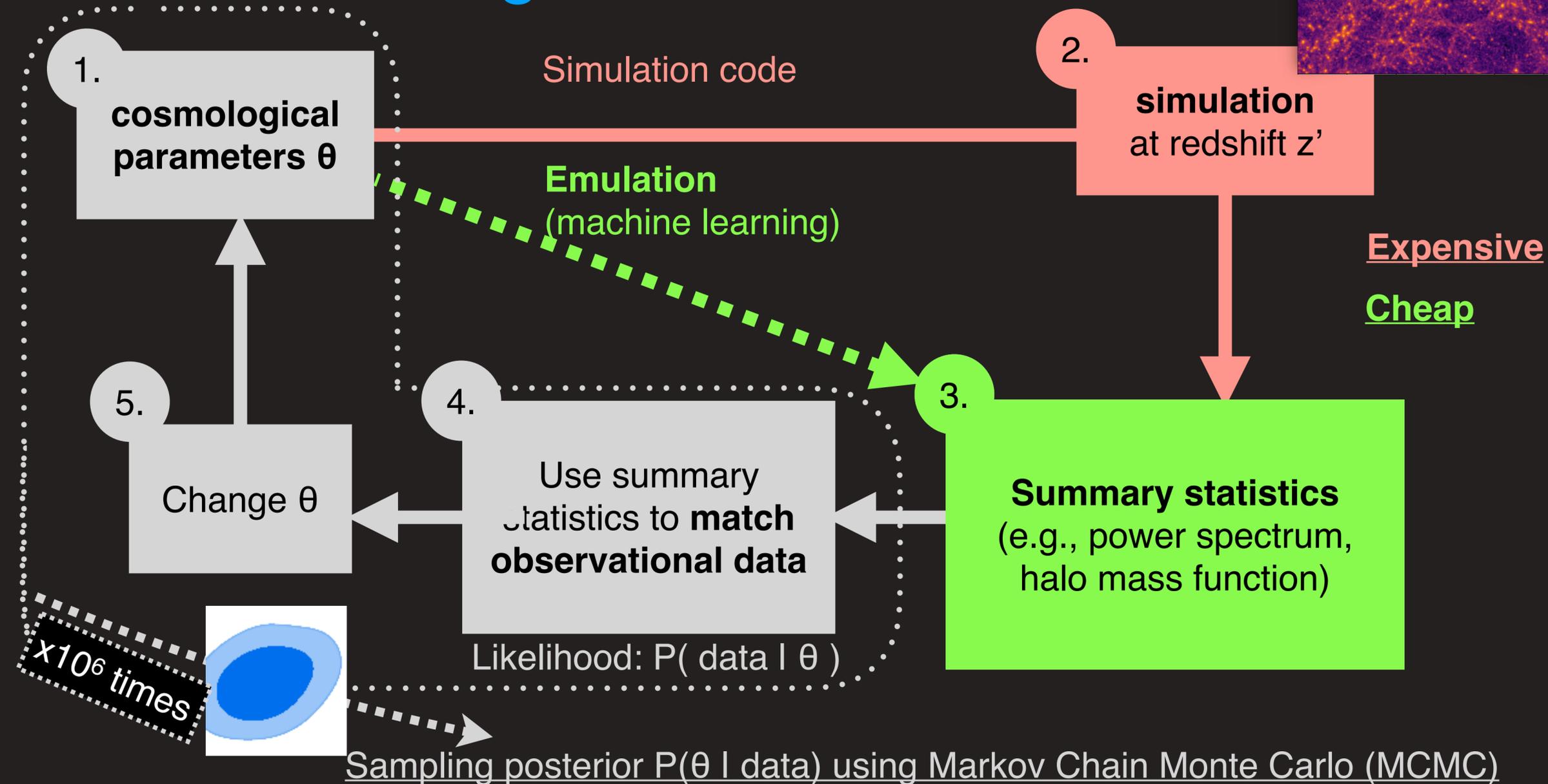
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MCMC using forward simulations: require $\sim 10^6$ simulations

What's emulation?

Bayesian inference using simulations



- Slide 4: figures b big as th also em simulation do this it simulation

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-

MCMC using forward simulations: require $\sim 10^6$ simulations

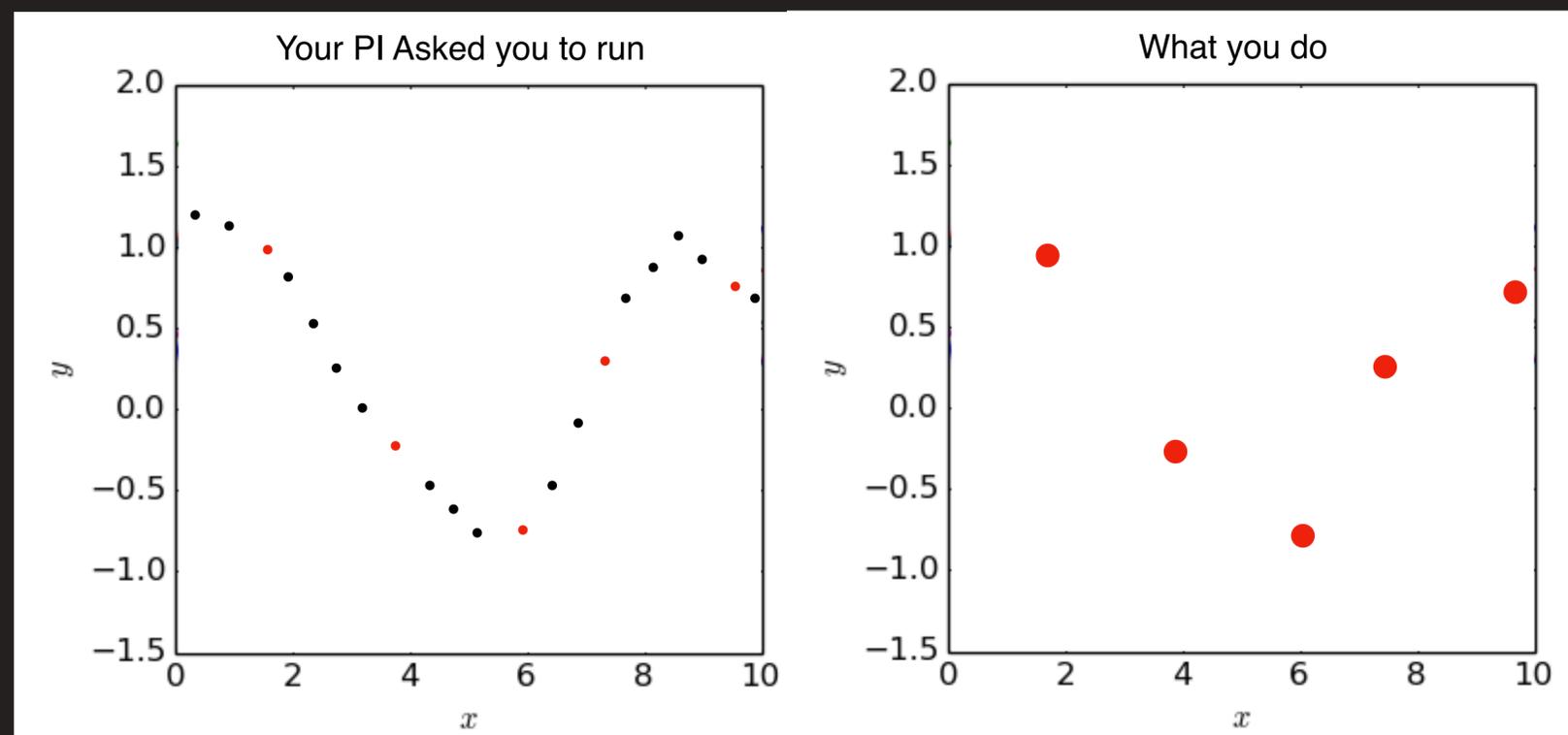
MCMC using emulation: require $\sim 10^2$ simulations

image credit: wiki, cobaya

What's emulation?

Reducing time on exploring parameter space

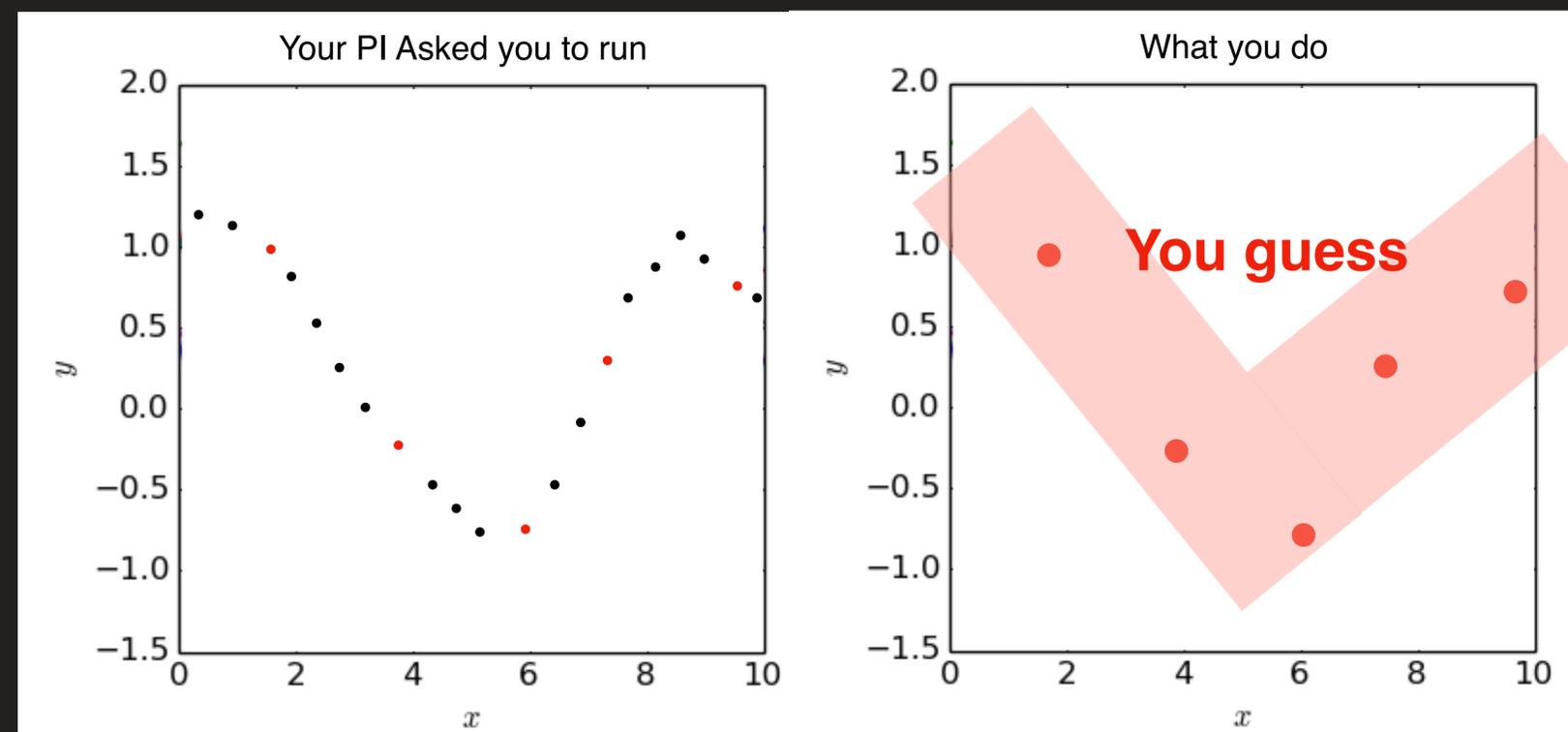
- The everyday scenario
 - Your PI asks you to run 20 simulations before next meeting
 - ... but you only have time to run 5 simulations.



What's emulation?

Reducing time on exploring parameter space

- The everyday scenario
 - Your PI asks you to run 20 simulations before next meeting
 - ... but you only have time to run 5 simulations.



What's emulation?

It's your *Bayesian* prior/posterior

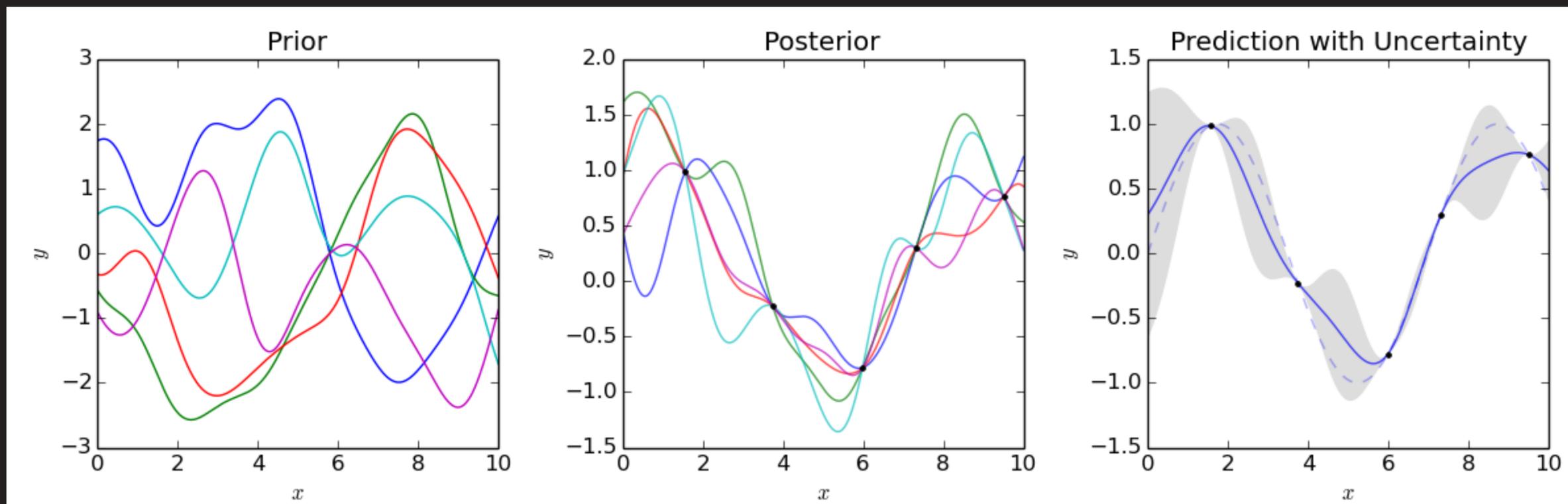
Emulation =

Posterior predictions given *Prior* and *Data*

↓
Simulations you haven't run

↓
A distribution over smooth functions

↑
Simulations



- **Gaussian process prior:** Smoothness features of $y(x)$ before data are collected.

What's emulation? Cosmic calibration

- Key ingredients for emulation:

- Surrogate modelling: **interpolation**
- Experimental design: **space-filling**

- Better d
- How do

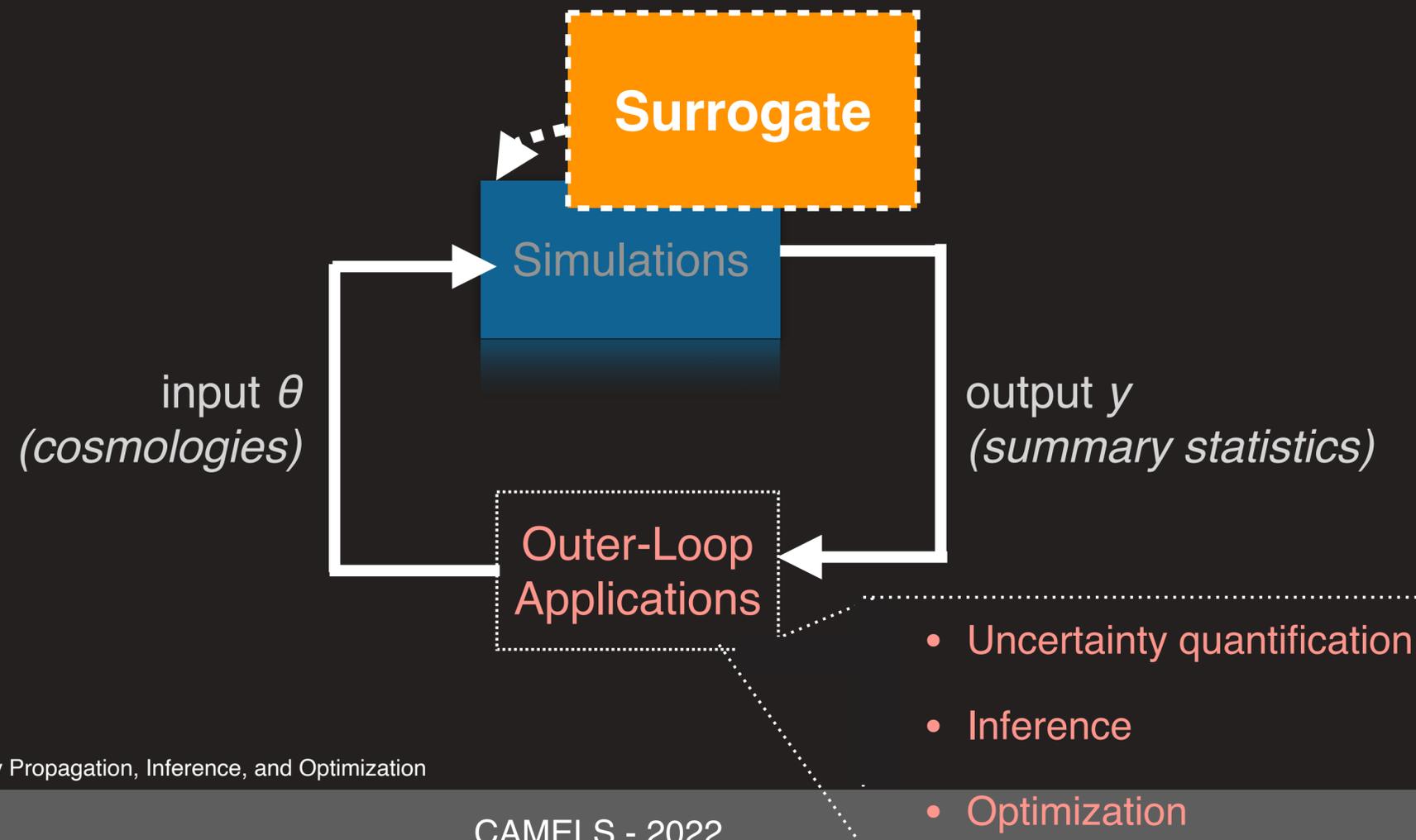


Illustration credit: Perherstorfer et al (2018)
Survey of Multifidelity Methods in Uncertainty Propagation, Inference, and Optimization

What's emulation? ~~Cosmic calibration~~

Bayesian calibration for computer experiments

- Key ingredients for ~~emulation~~ *Bayesian* modeling:
 - Surrogate modelling: ~~interpolation~~ **Prior**
 - Experimental design: ~~space-filling~~ **Data**

Emulation =

Posterior predictions given *Prior* and *Data*

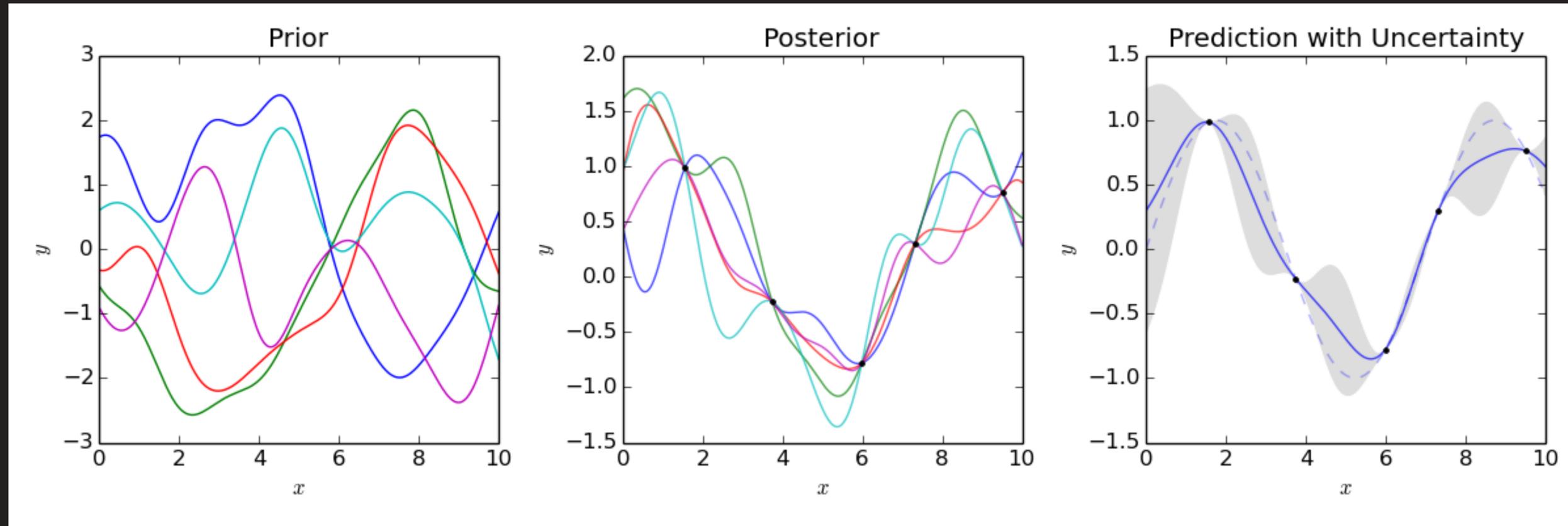
↓
Simulations you haven't run

↓
A distribution over
smooth functions

Simulations



Gaussian process: Bayesian function prediction



- **Gaussian process prior:** Smoothness 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.*

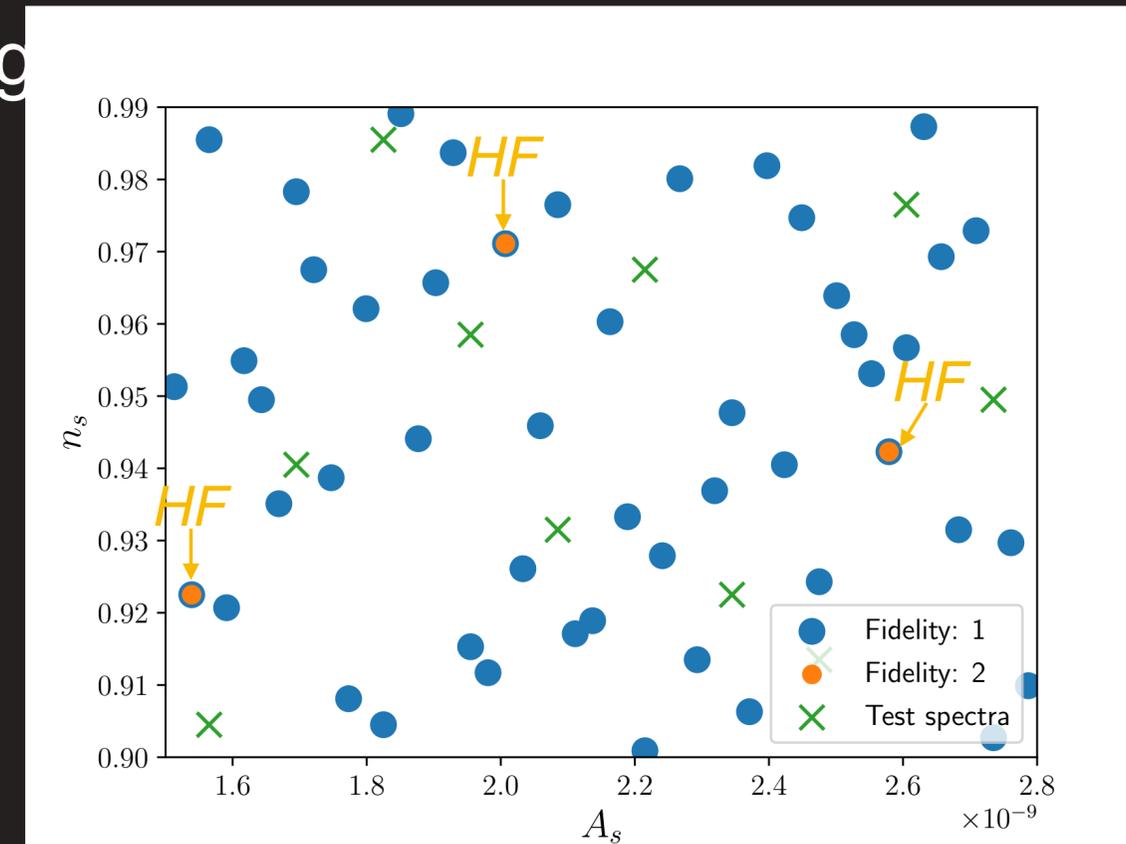
image credit: wikipedia

* This Bayesian attitude is mentioned in Santner (2003), The Design and Analysis of Computer Experiments

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

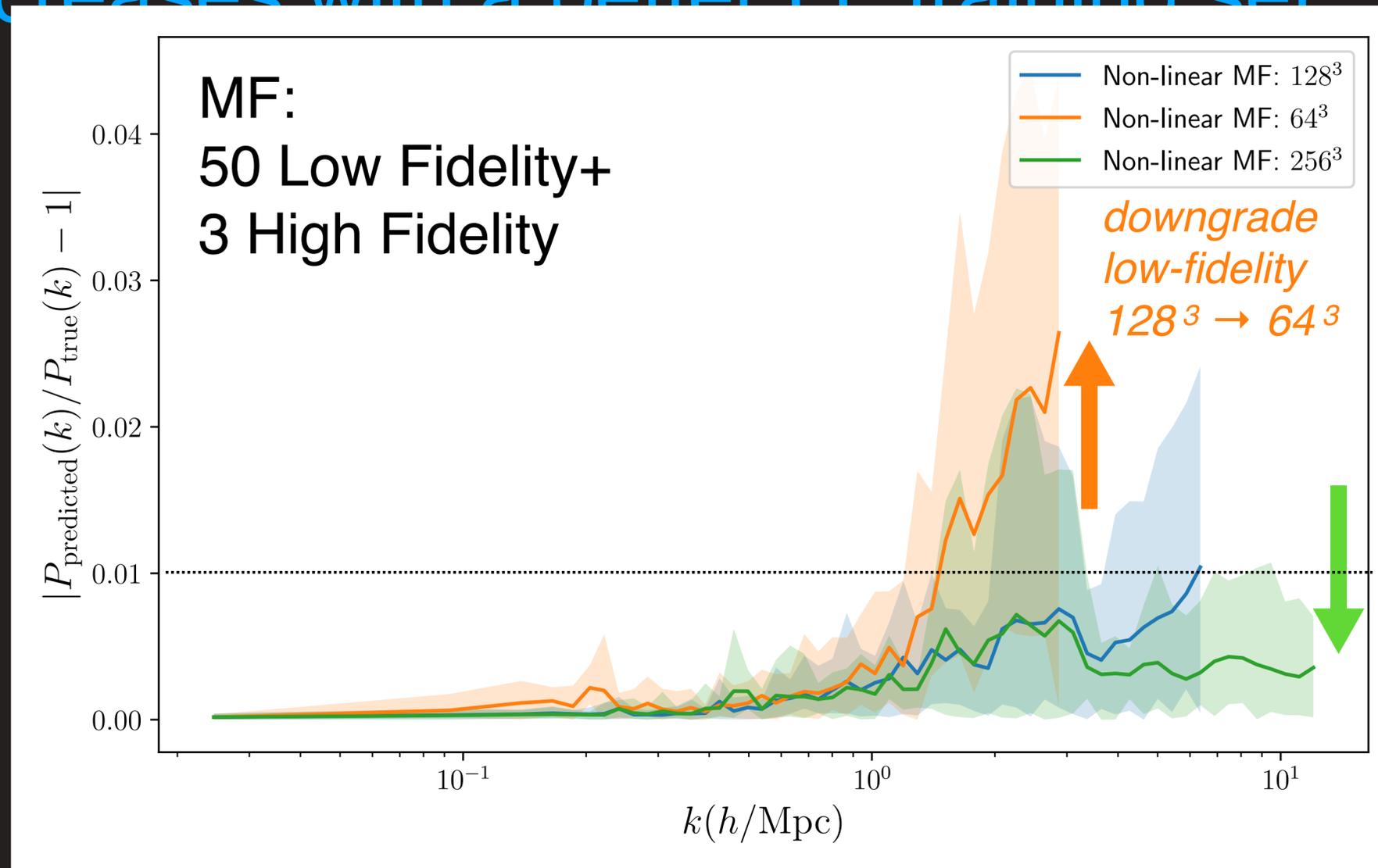


Ho, Bird, Shelton (2022)

- This looks like a
- Draw arrows to help people understand
- Prior volume is large here but can put constraints
- Stress the importance of improving
- Optimize the interpolation

Example 1: matter power spectrum

Accuracy increases with a better LF training set

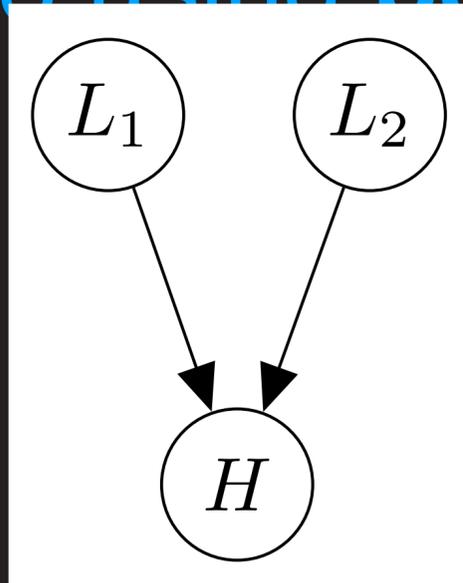


- The quality of LF simulations affects the accuracy of MF emulation
- Small scales emulation can be improved with a better quality of LF simulation suite. → *Question: Can we use small box LF to improve emulation?*

- This accuracy
- Someone the 64^3 accuracy
- The point design budget accuracy versatility

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.

- Did not

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

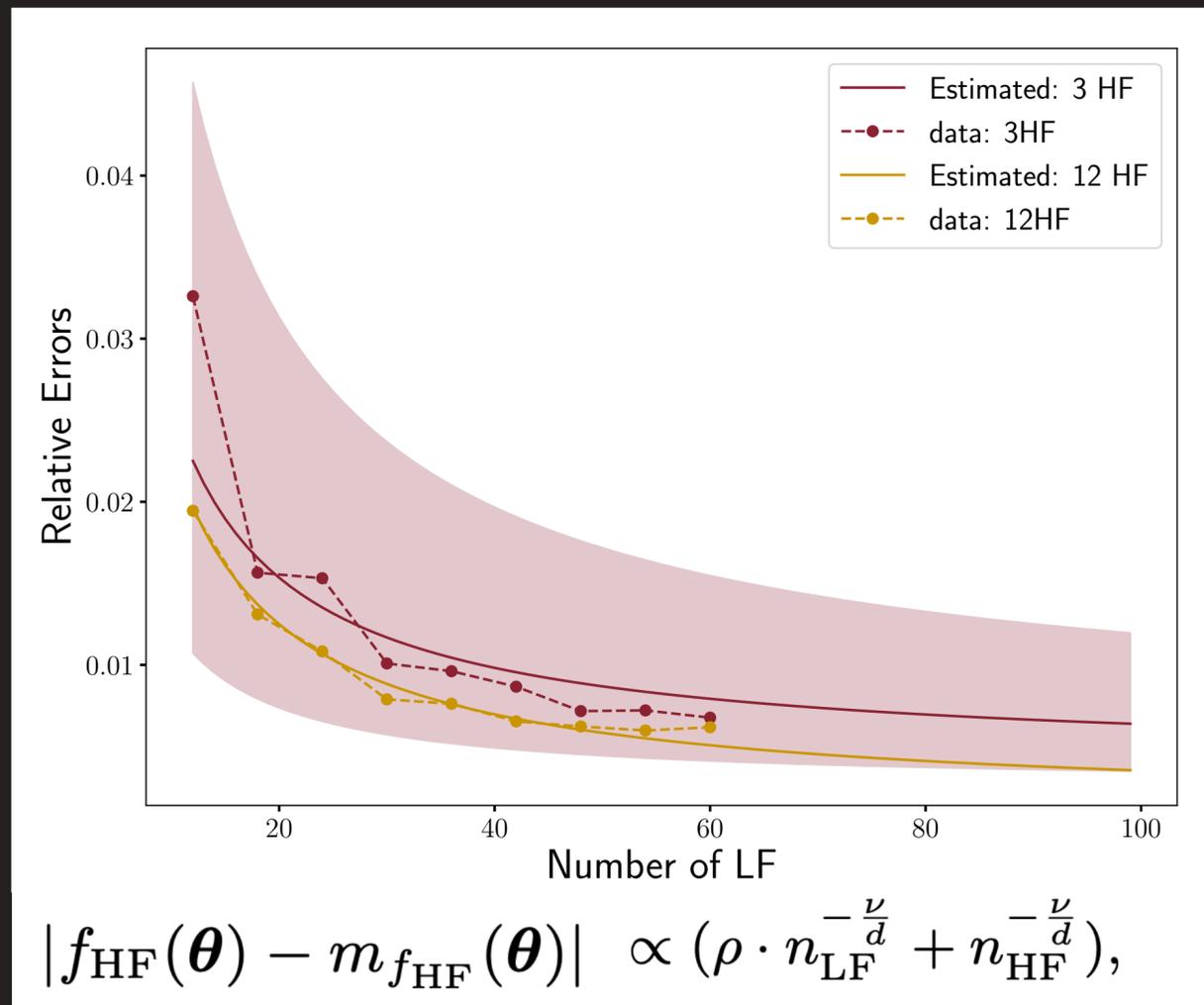
• K_{LIN} : Linear kernel, doing Bayesian linear regression

GMGP: Ji (2021)

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

Example: matter power spectrum Error analysis & optimal design

- Emulation error roughly scales as a **power law**
- Solve the Lagrangian multiplier with a fixed budget gives you the **optimal design**:



$$n_{\text{HF}} \propto \left(\frac{1}{C_{\text{HF}}} \right)^{\frac{d}{\nu+d}}$$

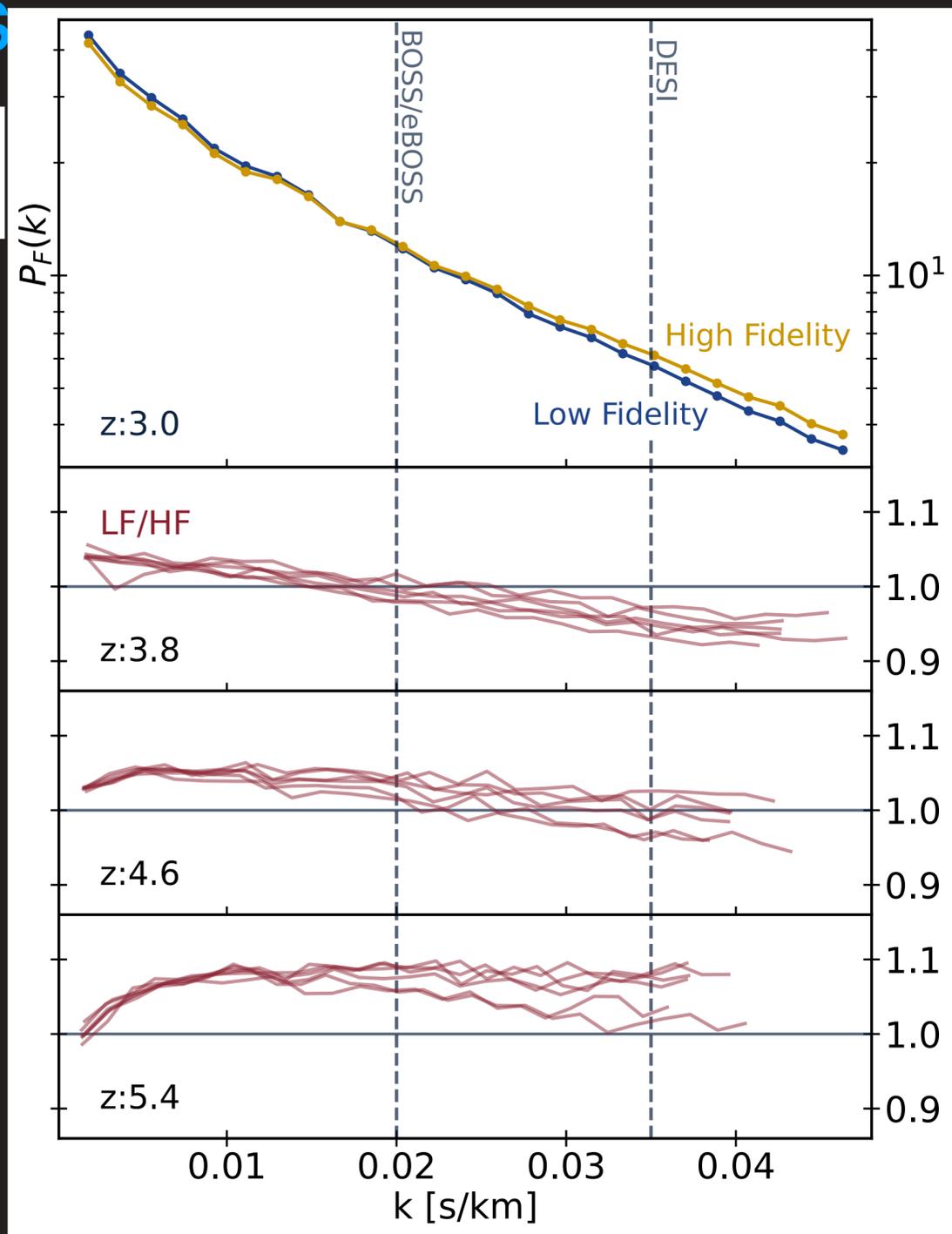
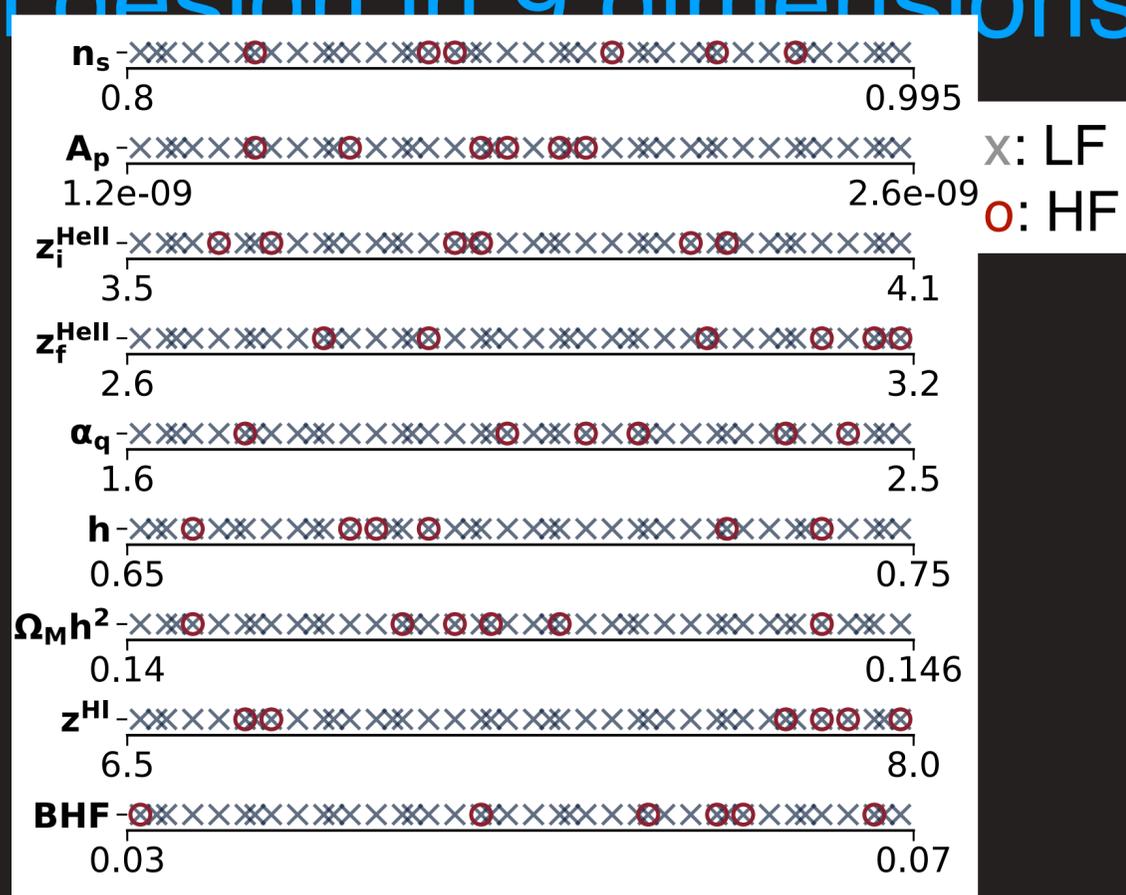
$$n_{\text{LF}} \propto \left(\frac{\rho}{C_{\text{LF}}} \right)^{\frac{d}{\nu+d}}$$

- n_{HF} : number of HF simulations
- C_{HF} : cost of a HF simulation
- ρ : correlation between LF and HF

Theoretical basis: Wendland (2004), Ji (2021)

Example 3: Ly α flux power spectrum

Experimental design in 9 dimensions

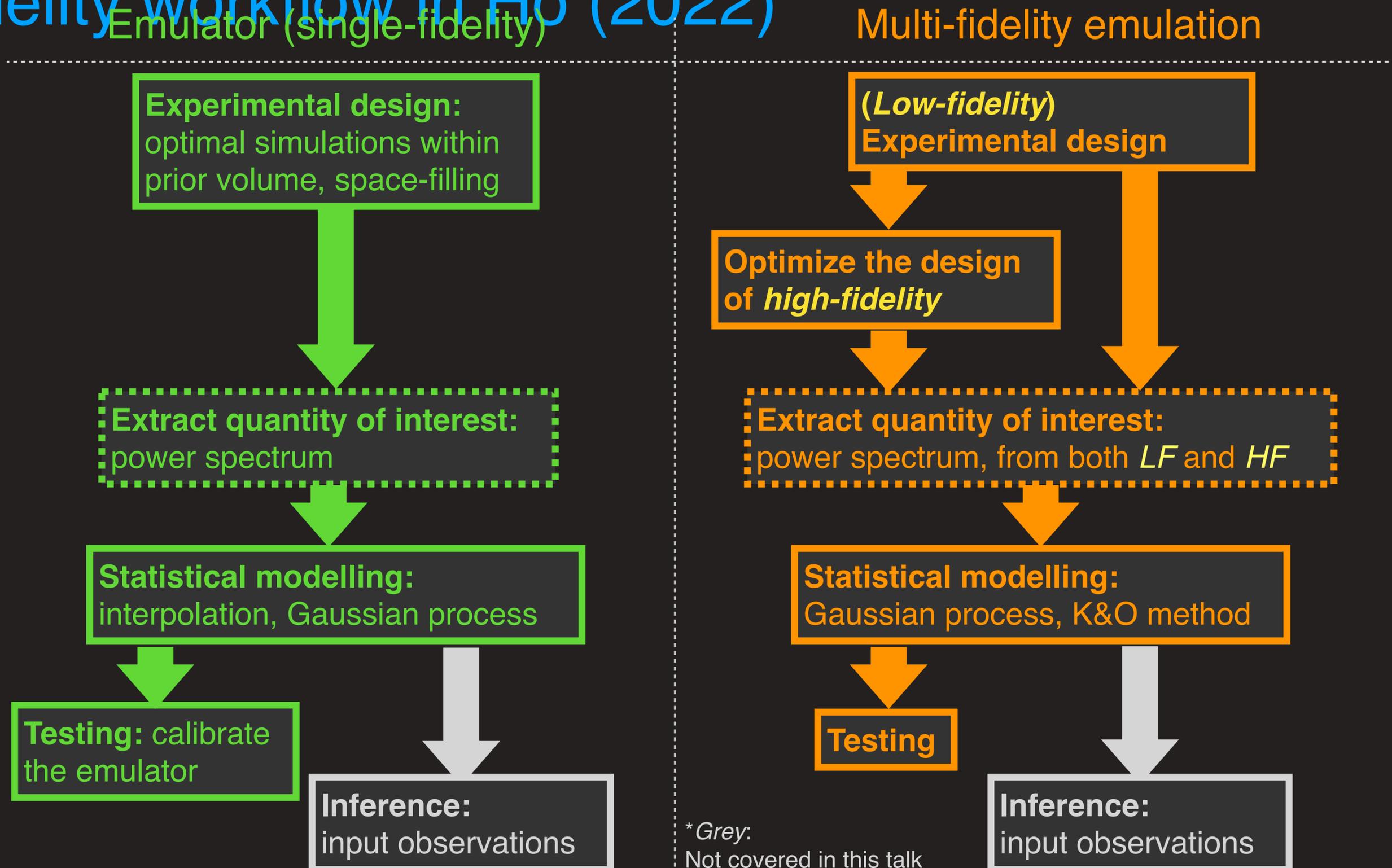


- 9 parameters ($z = 2 - 5.4$), including reionization parameters and black hole feedback
- The discrepancy between LF/HF appears across scales (k), varies with redshifts

figure credit: Martin Fernandez

What's multi-fidelity?

Multi-fidelity workflow in Ho (2022)



- Looks a
- Kind of Heitma
- not sur

Non-linear (NARGP) or linear (KO)?

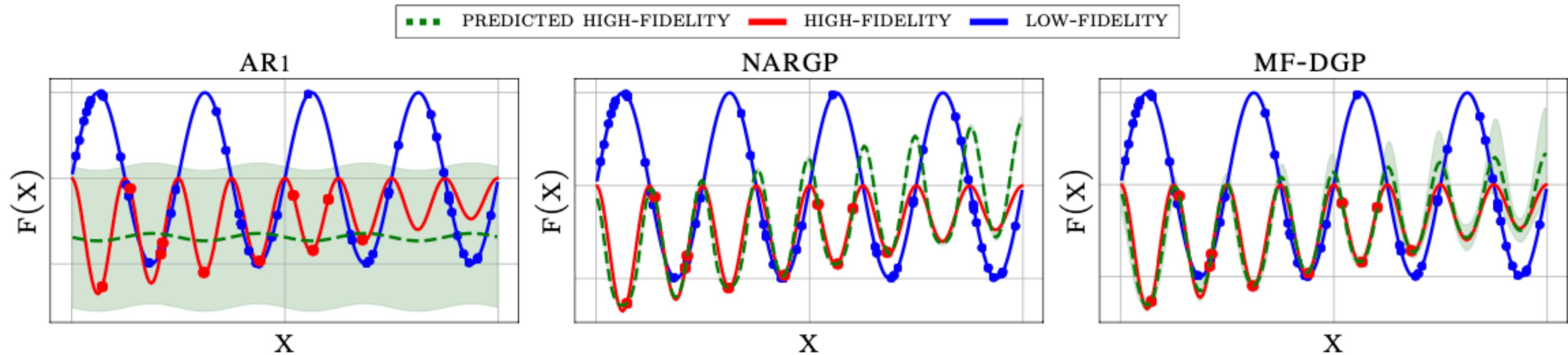


Figure 1: Limitations addressed and resolved jointly by our proposed MF-DGP architecture. Blue and red markers denote low and high-fidelity observations respectively. Shaded regions indicate the 95% confidence interval.

Uncertainty quantification depends on kernel choice

fig: Cutajar et al. - 2019 - Deep Gaussian Processes for Multi-fidelity Modeling