

# Uncertain theory predictions and Gaussian emulation of likelihoods

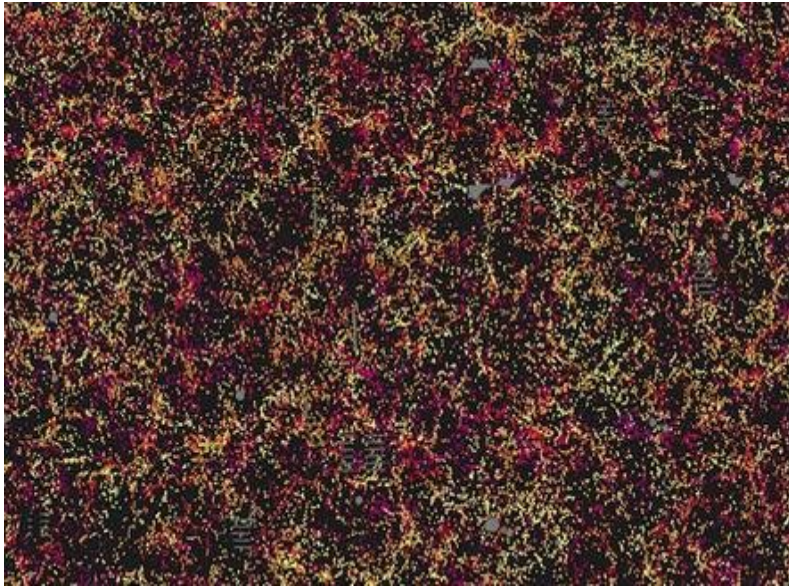
Marcos Pellejero Ibáñez, Giovanni Arico, Raul Angulo, Matteo Zennaro, Sergio Contreras...

Donostia International Physics Center (San Sebastián)

# Big Picture

- Go from:

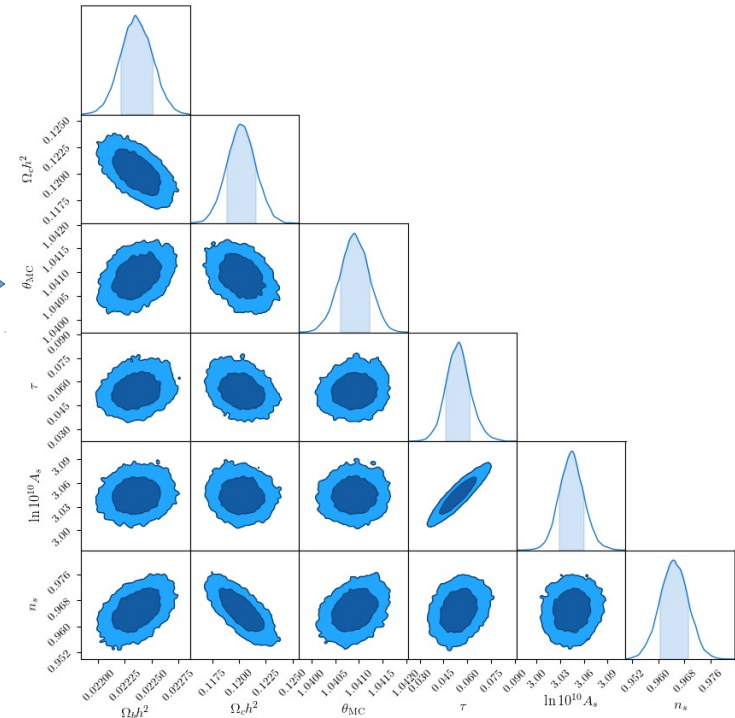
- To:



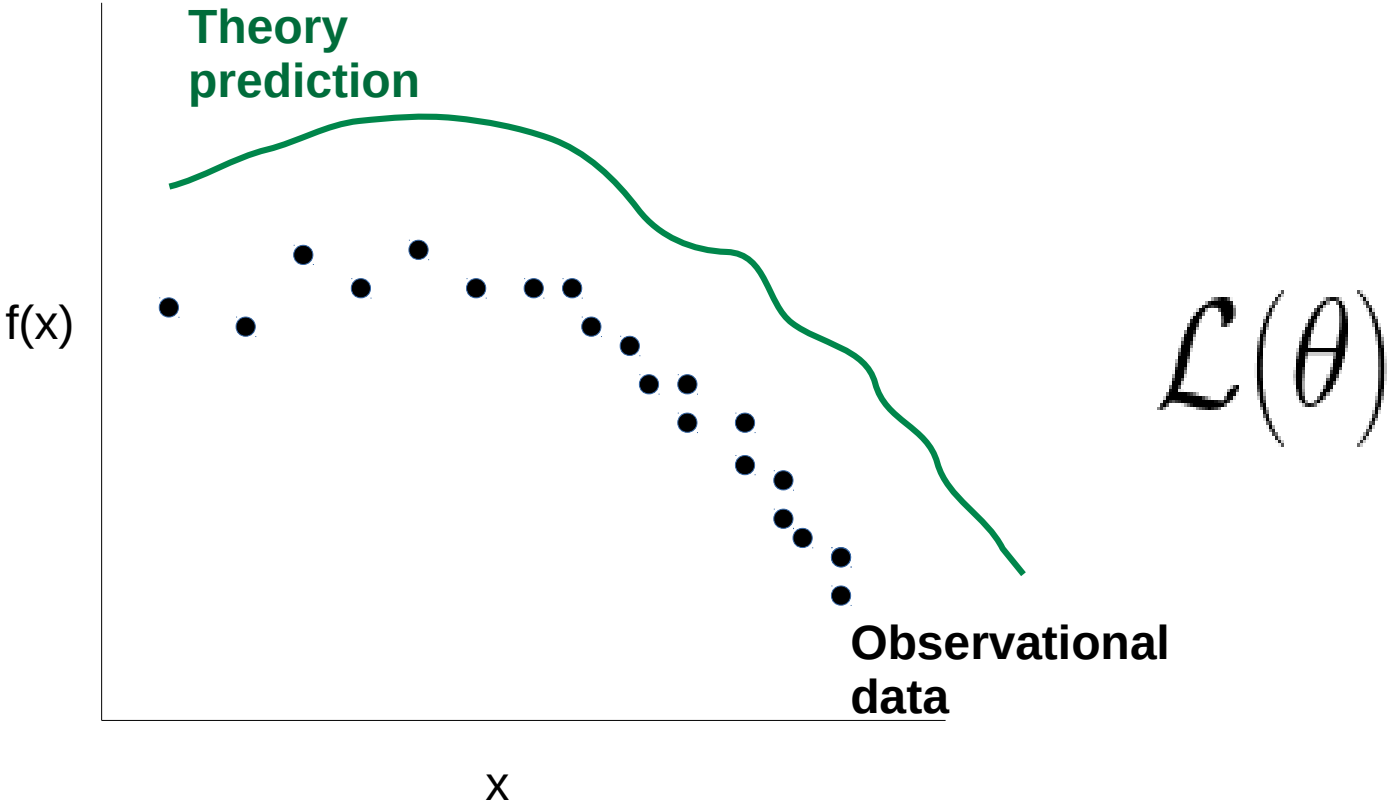
Credit Sloan Digital Sky Survey and its Baryon Oscillation Spectroscopic Survey



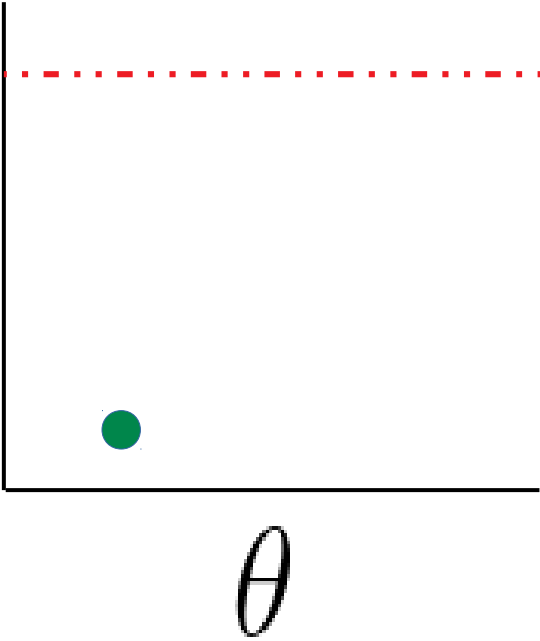
Likelihood function:  
Theoretical model



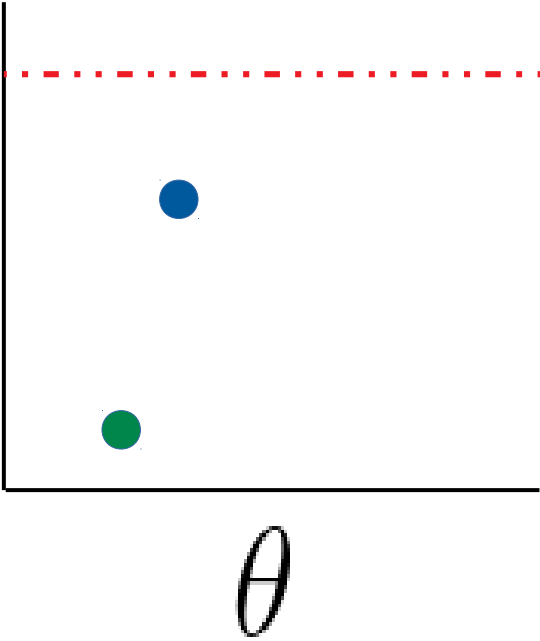
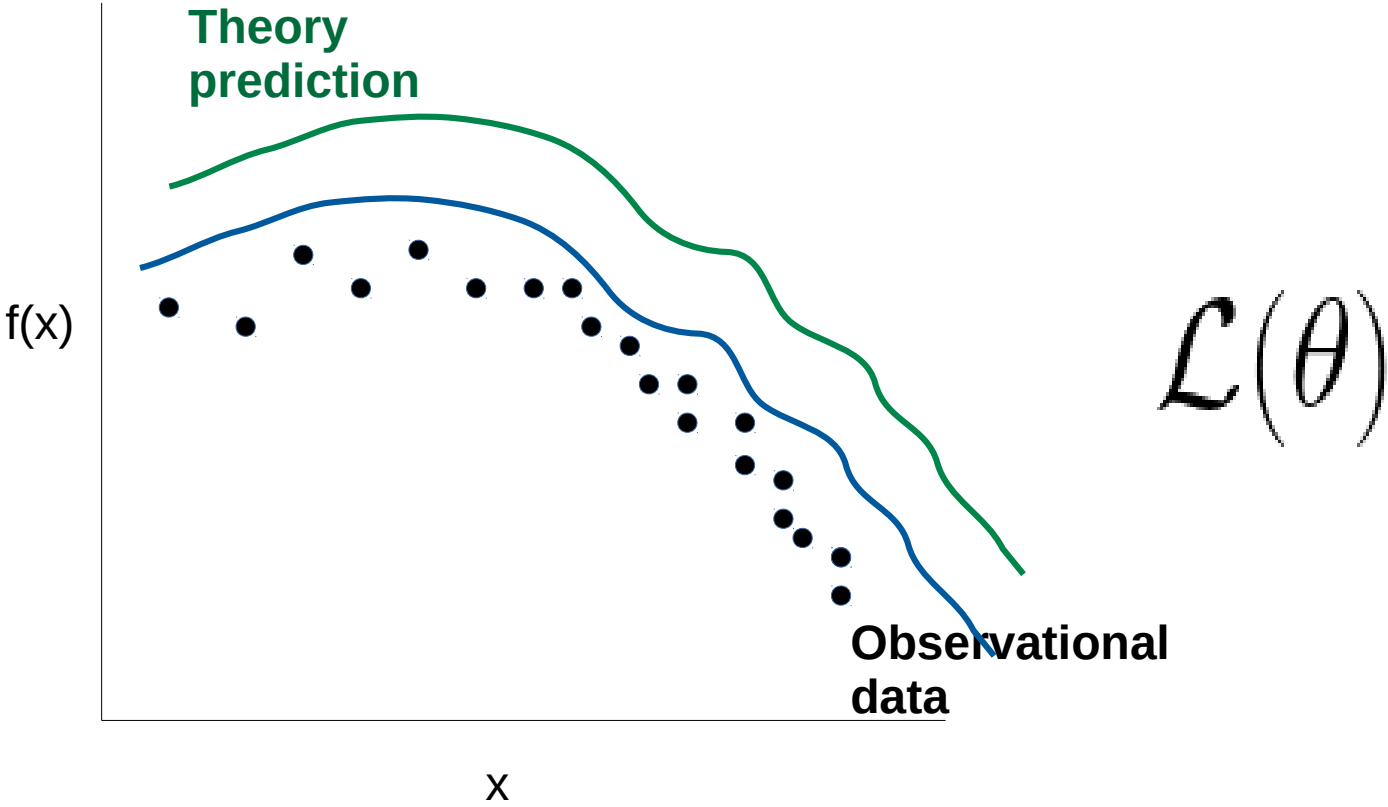
# Simple example



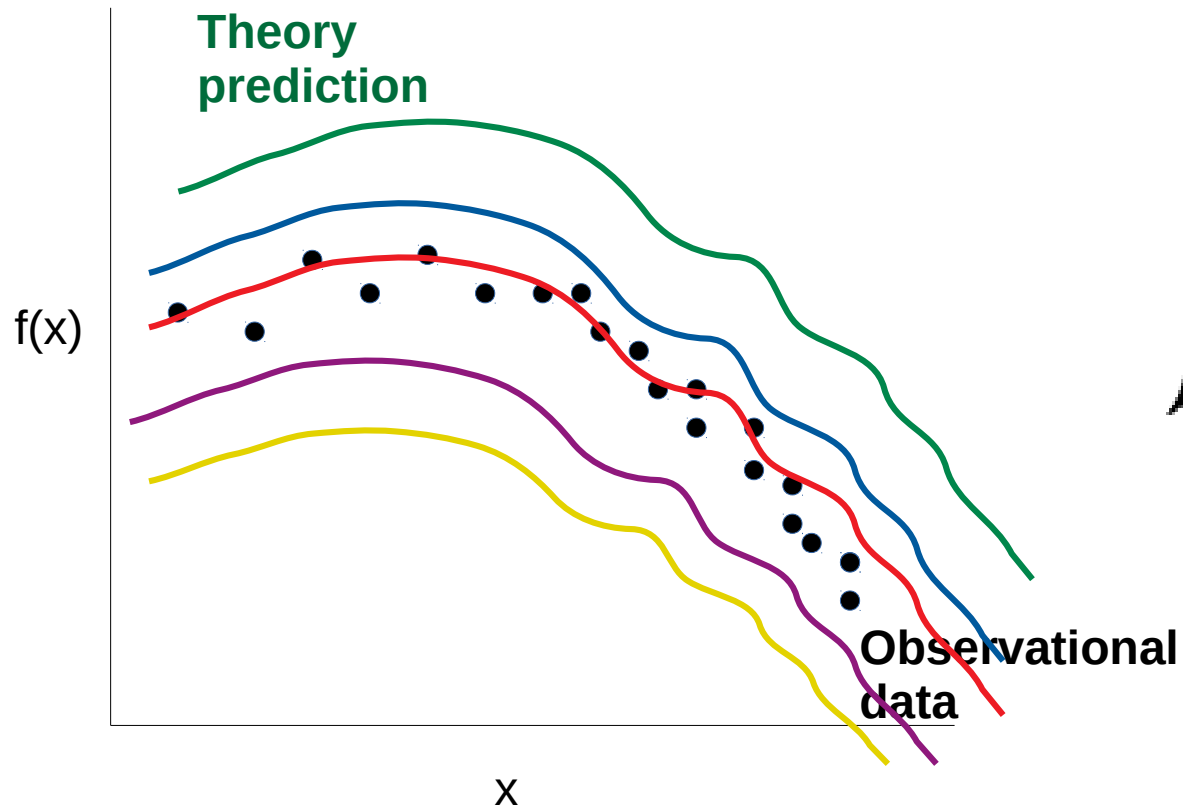
$$\mathcal{L}(\theta)$$



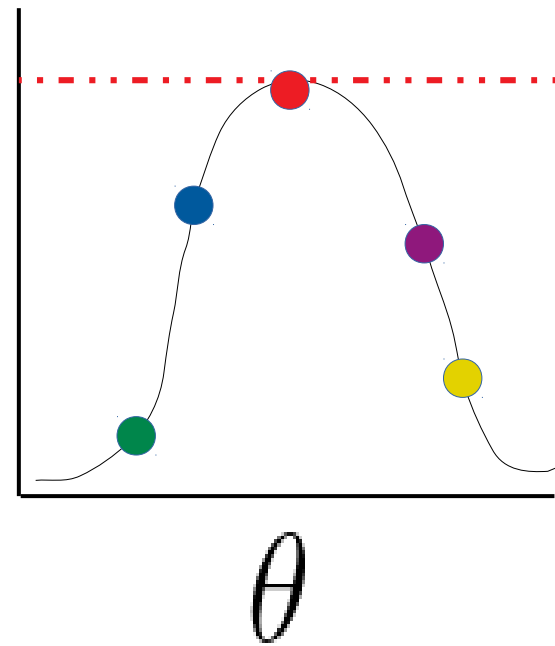
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$$\mathcal{L}(\theta)$$



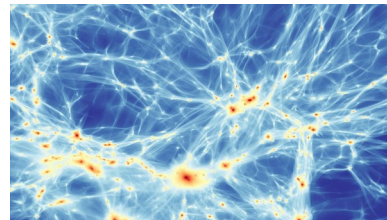
# Problems

**1) Expensive evaluations of the likelihood** (advance modeling).

Complicated loop evaluations, high-n integrals in PT, modeling observational effects



**Direct N-body simulations**



**2) Expensive posterior inferences.** Very long chains to achieve convergence, high dimensionality.

**3) Noisy evaluations.** Cosmic variance from simulations, uncertainties in the group finder or in the gravity solver.

Traditional MCMC not adequate

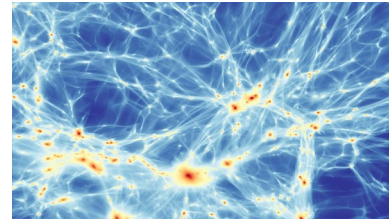
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**Direct N-body simulations**

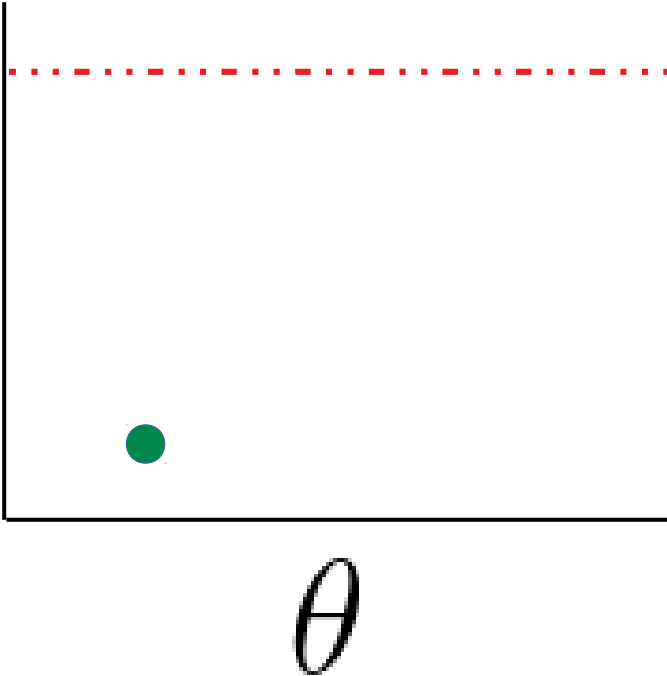
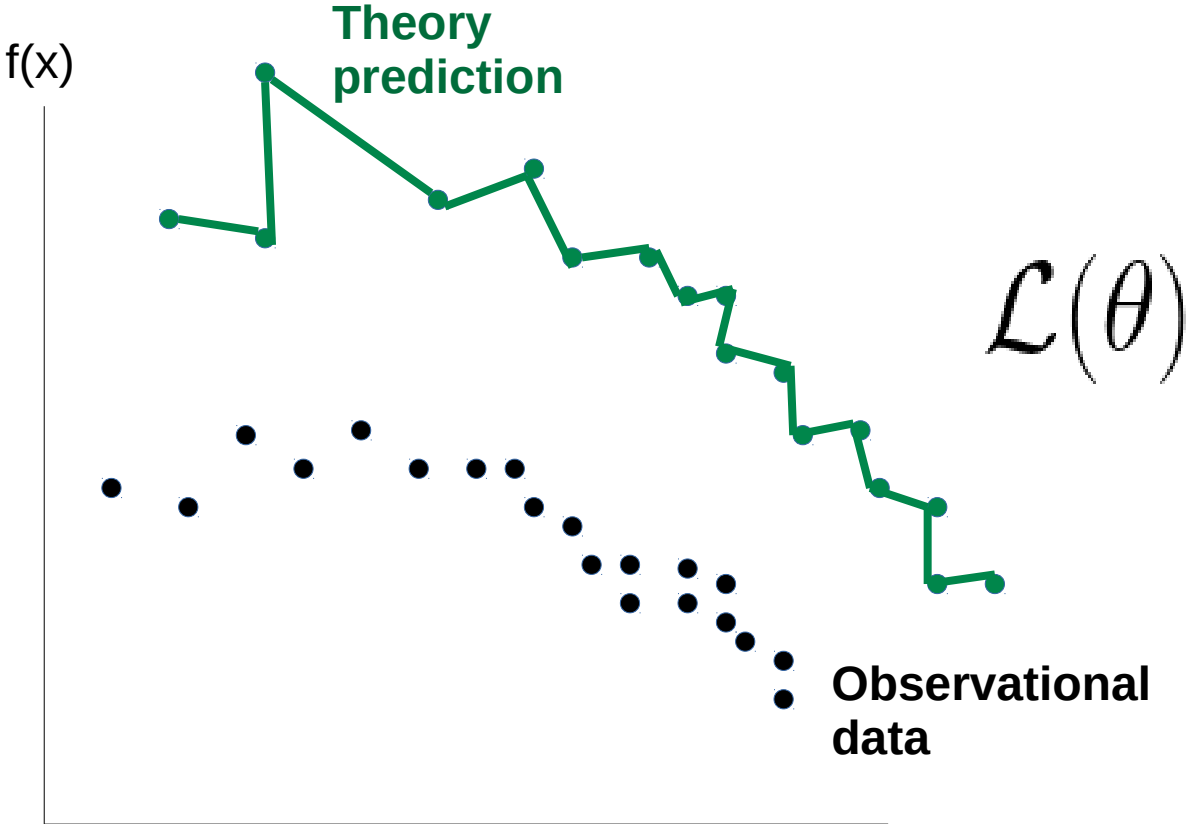


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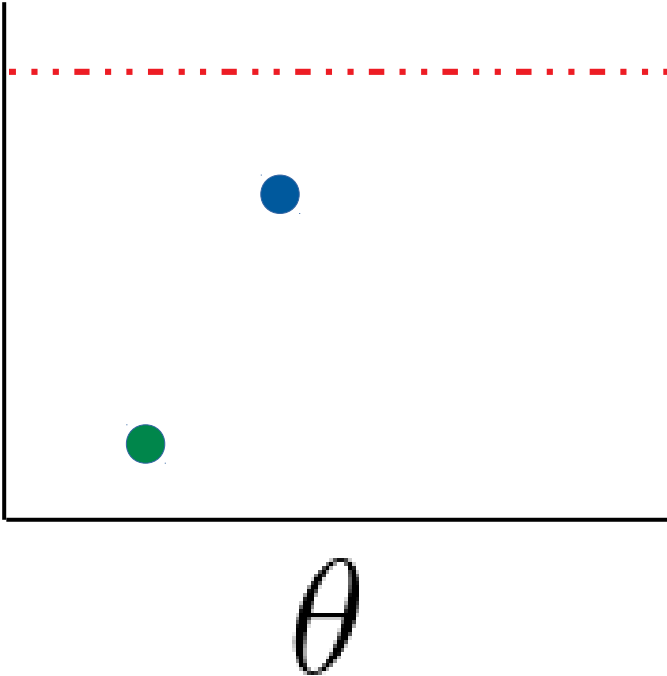
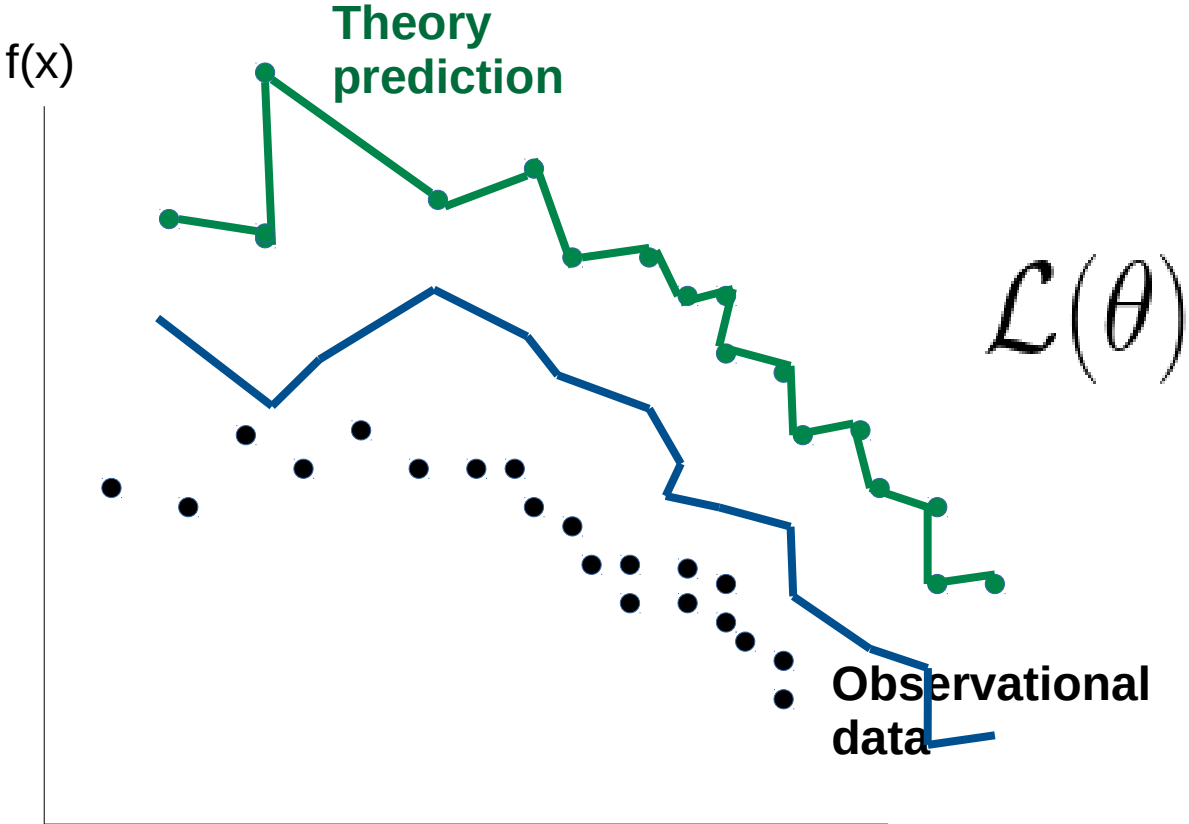
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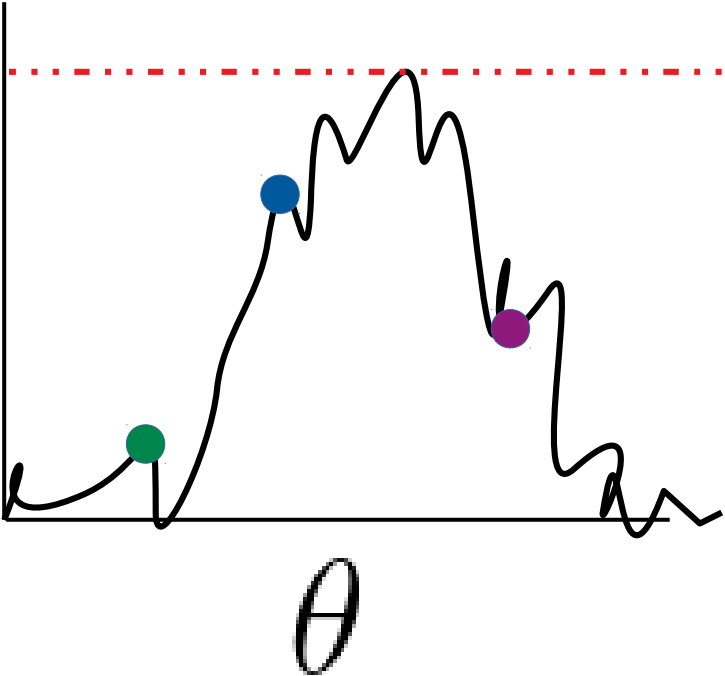
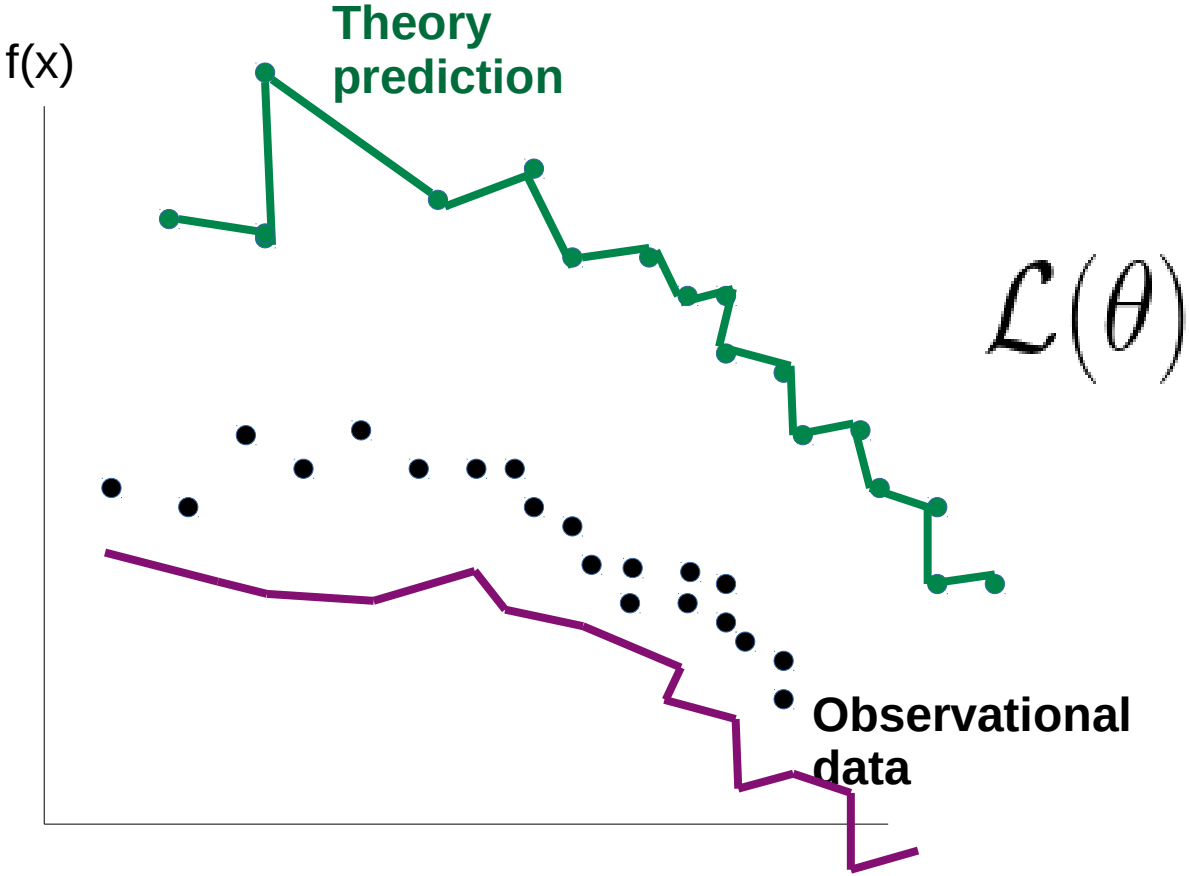




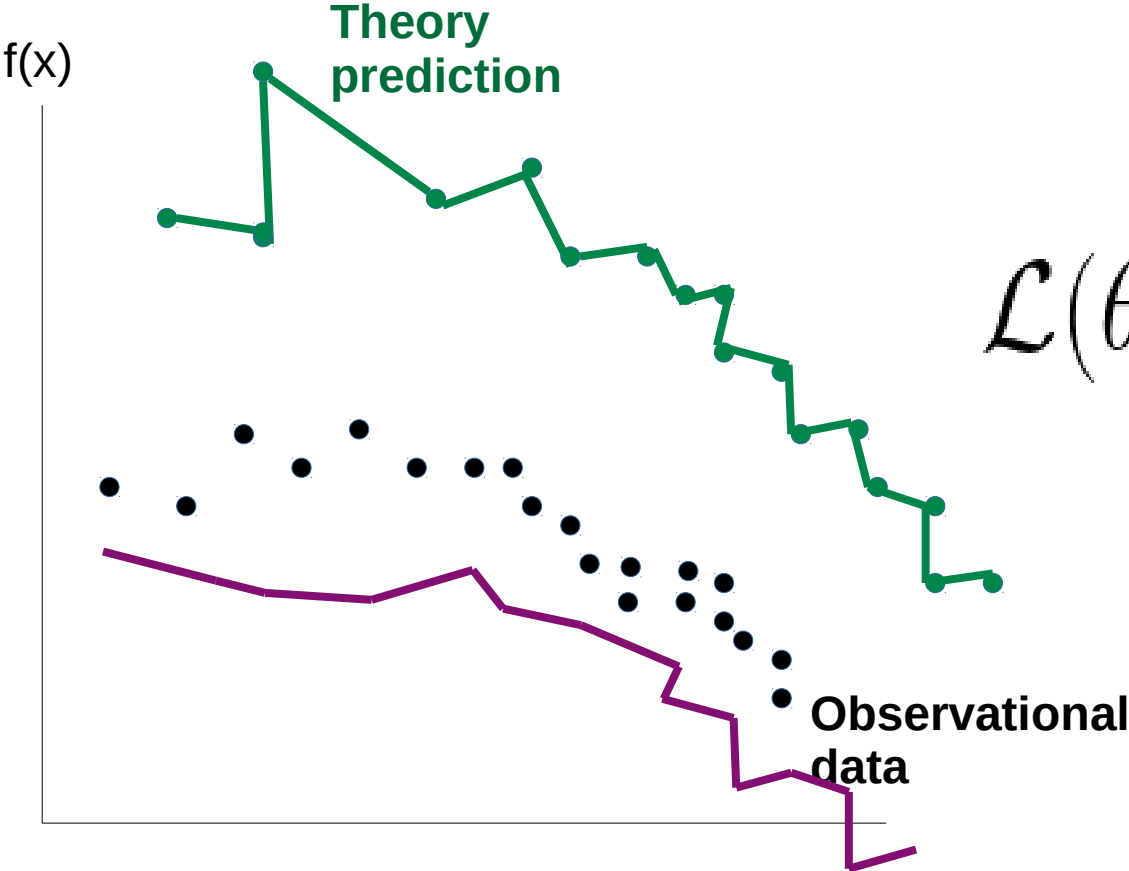
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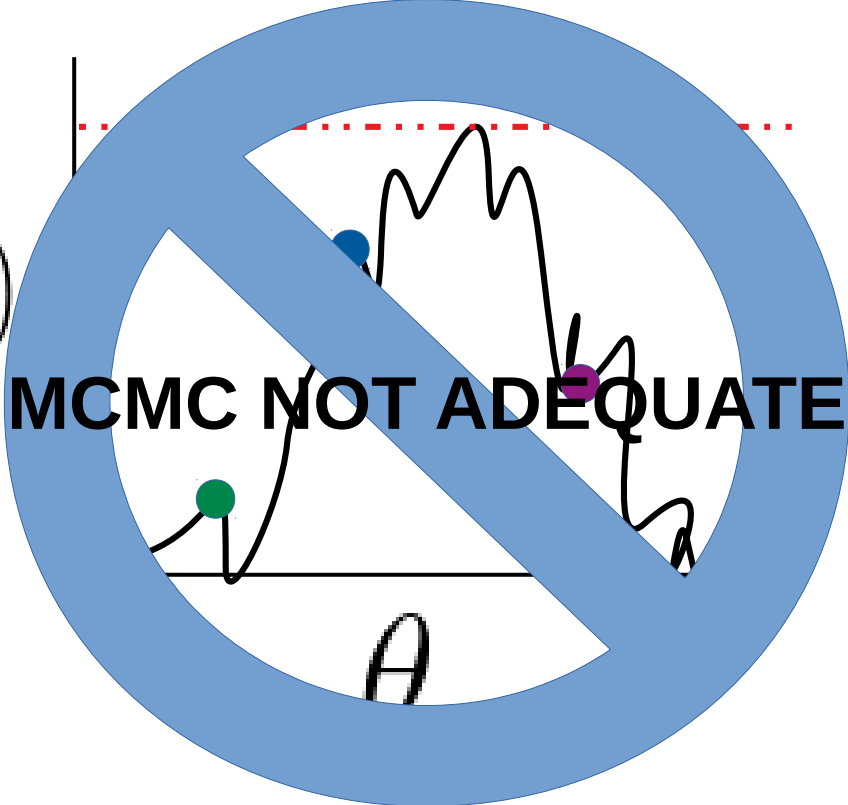
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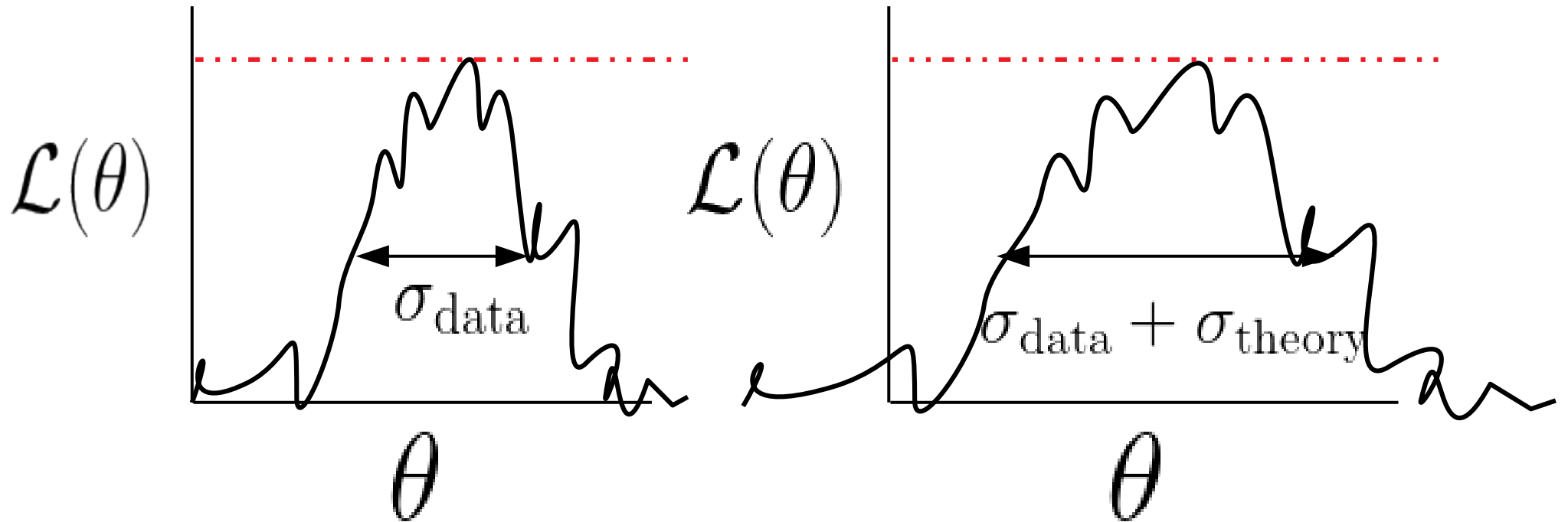
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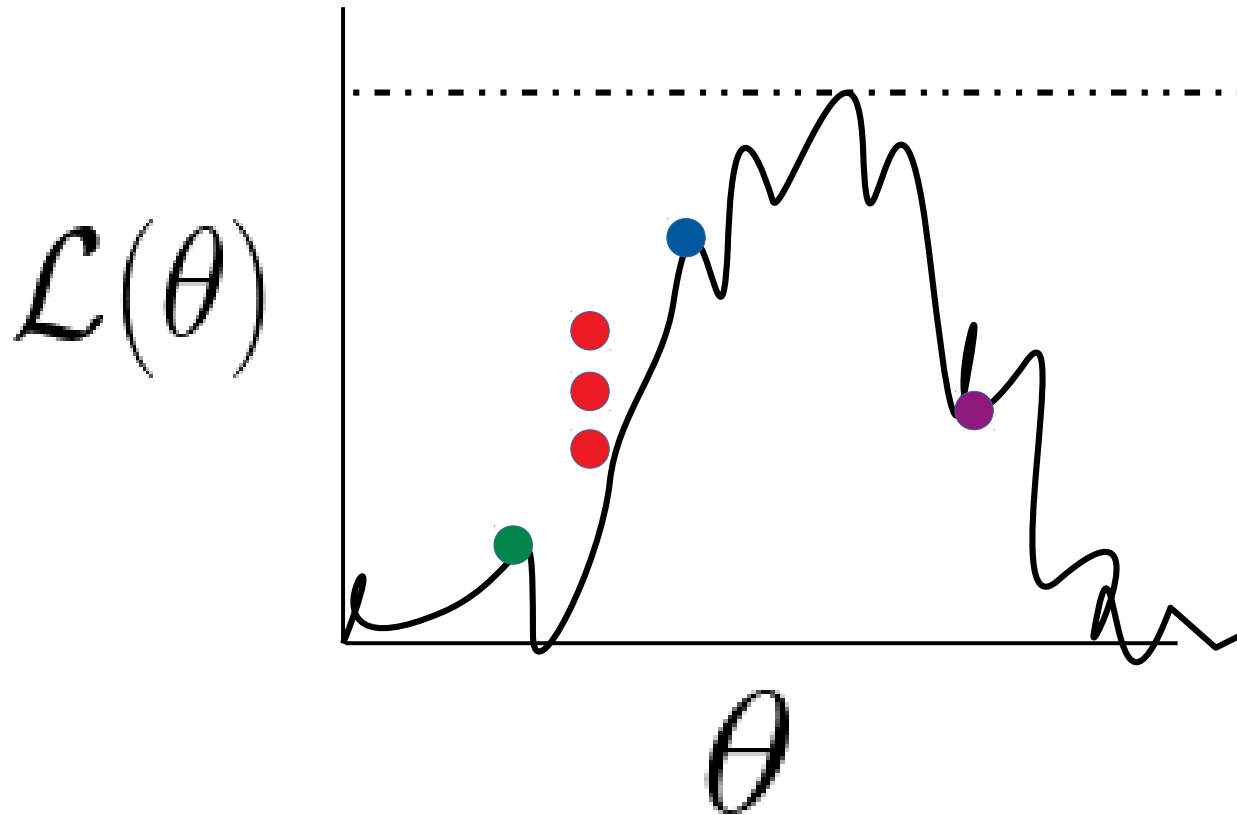
$\mathcal{L}(\theta)$



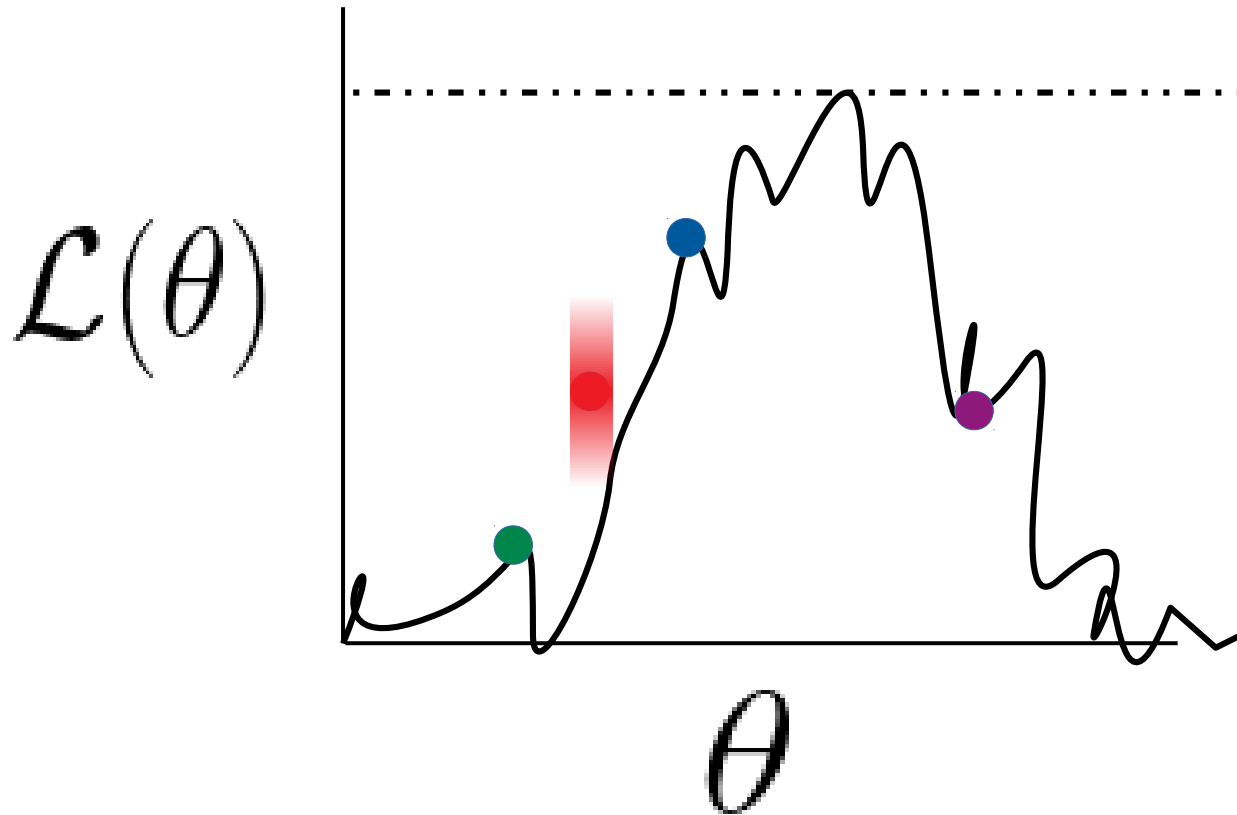
# 1) Include theory error



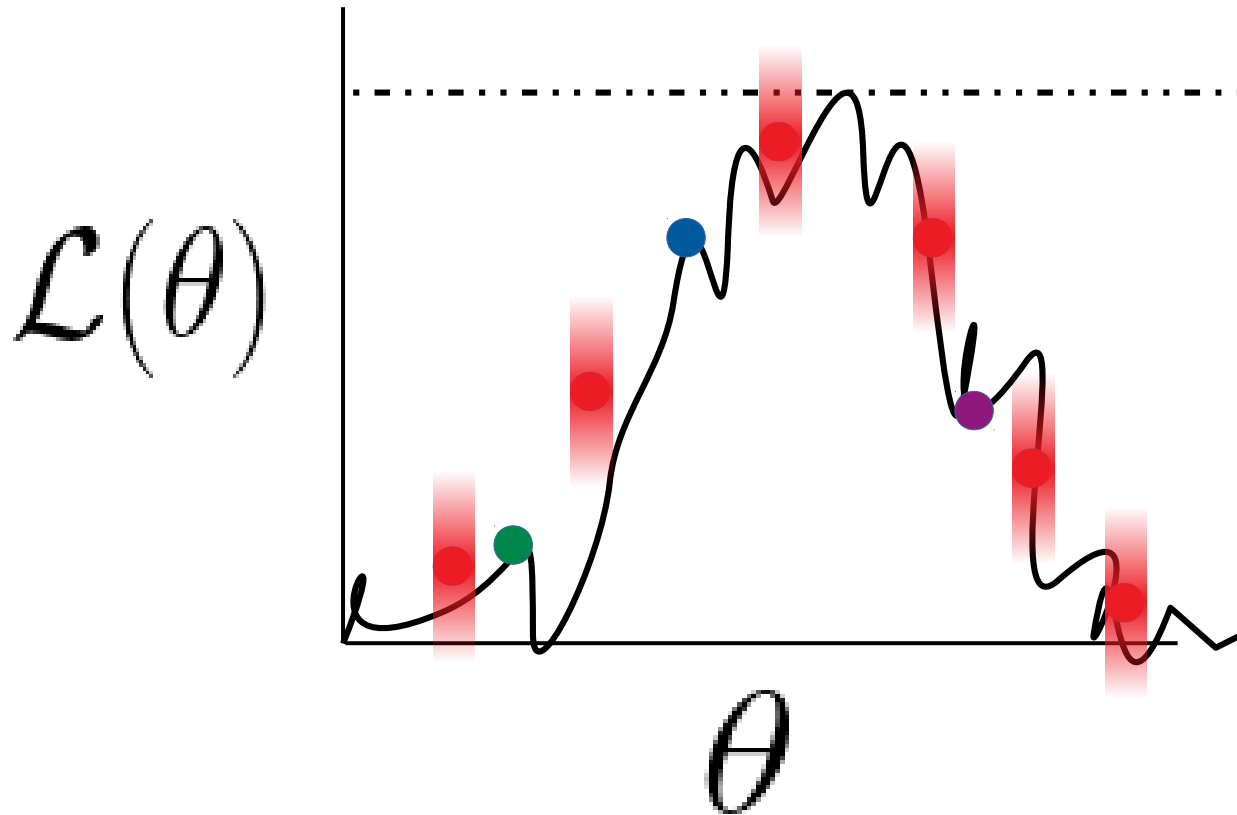
## 2) Reconstruction (regression) of the likelihood: Gaussian Process



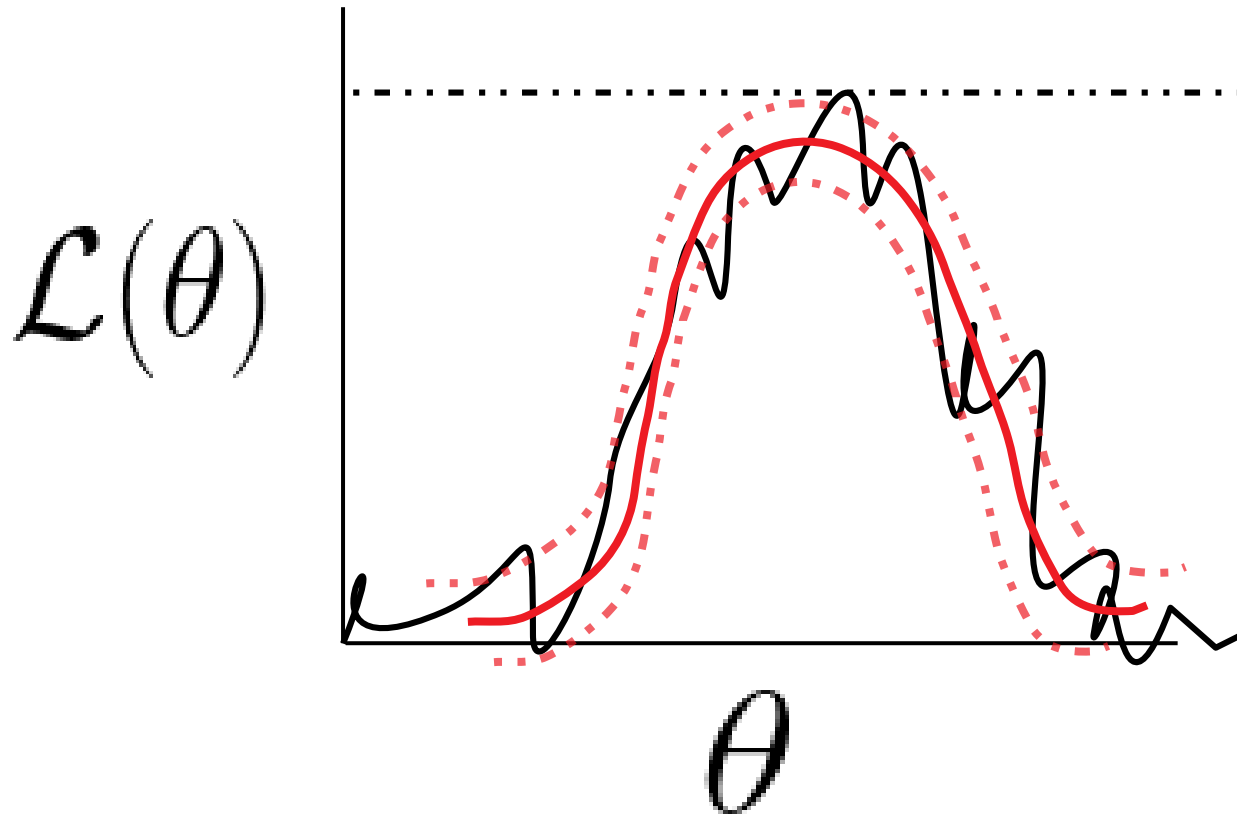
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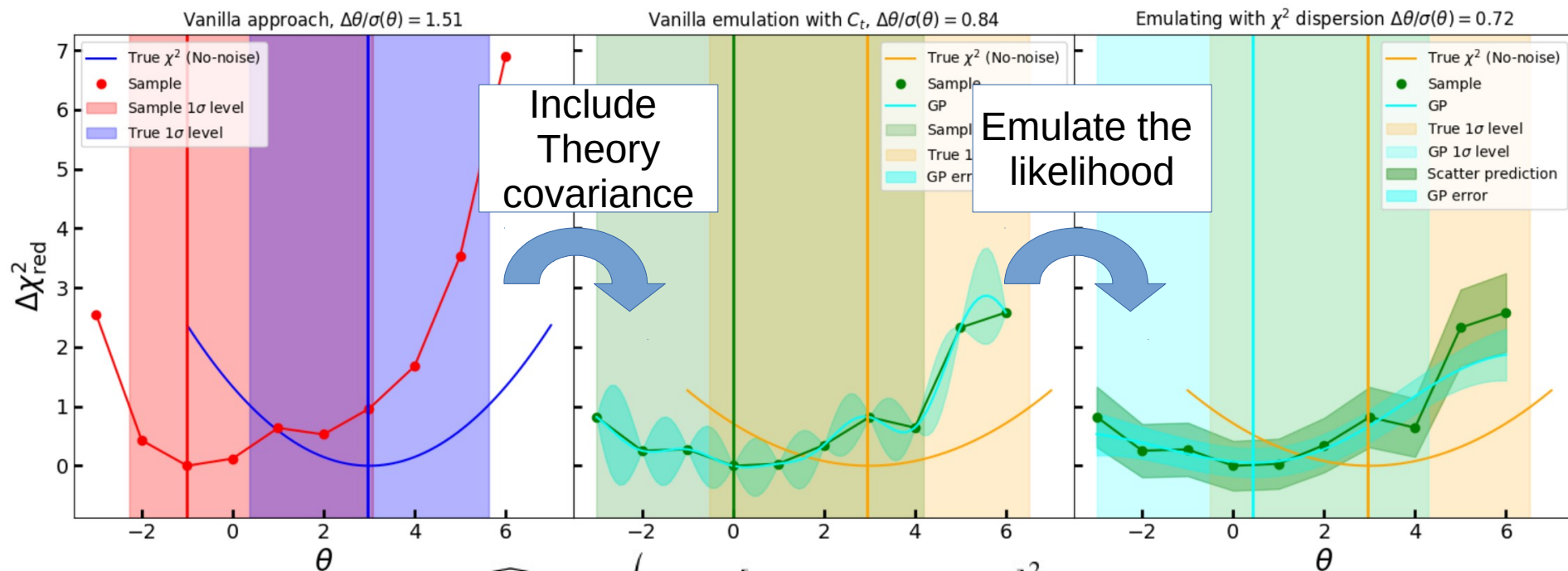


## 2) Reconstruction (regression) of the likelihood: Gaussian Process





# Noise on the likelihood function: toy model and Gaussian Process



$$X^T C^{-1} X \sim \mathcal{N}\left(n + \sum_i \left[ (C_d + C_t)_{ij}^{-1/2} (d - t)_j \right]^2, \right. \\ \left. 2n + 4 \sum_i \left[ (C_d + C_t)_{ij}^{-1/2} (d - t)_j \right]^2 \right).$$

Pellejero-Ibanez, Arico, et al. (in prep.)

# Problems

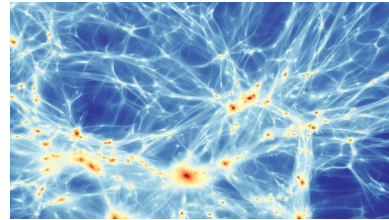
*Minimal amount of likelihood function evaluations to recover the true one?*

## 1) Expensive evaluations of the likelihood (advance modeling).

Complicated loop evaluations, high-n integrals in PT, modeling observational effects



### Direct N-body simulations

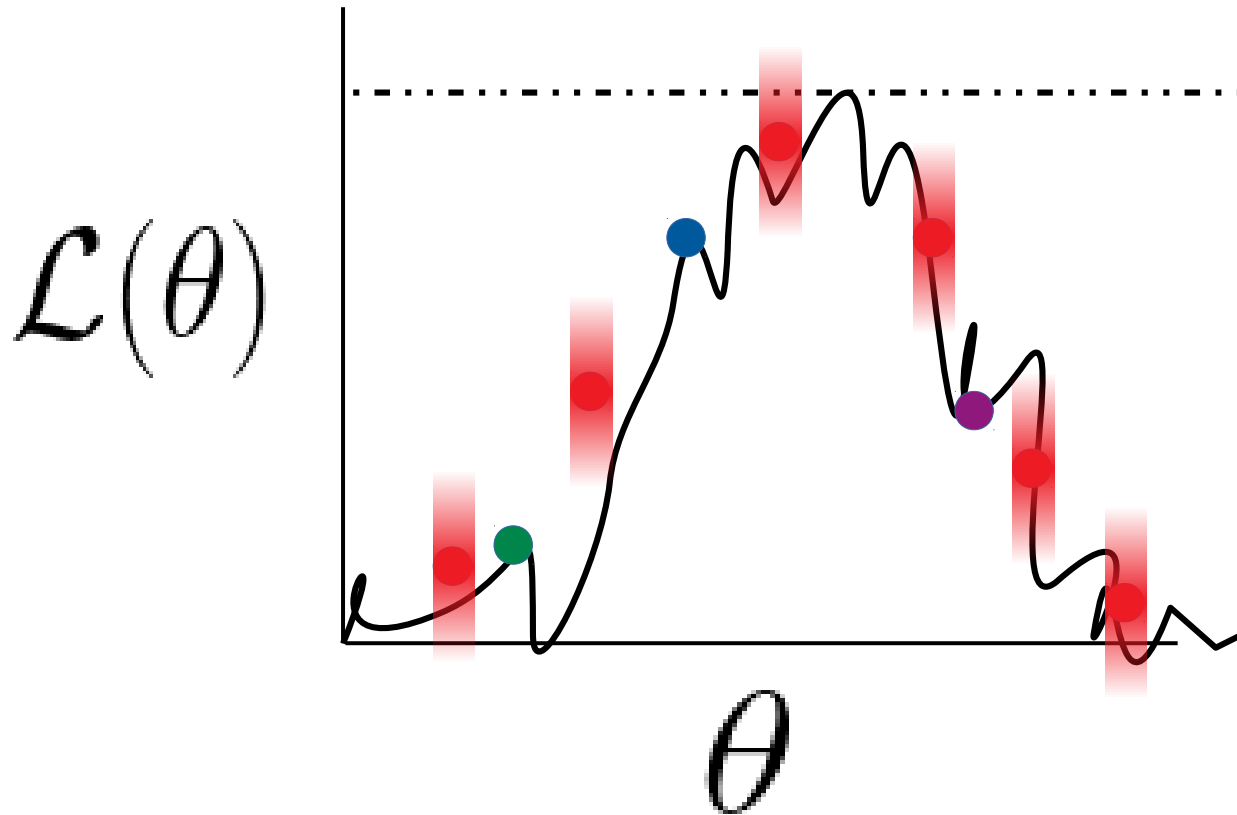


## 2) Expensive posterior inferences. Very long chains to achieve convergence, high dimensionality.

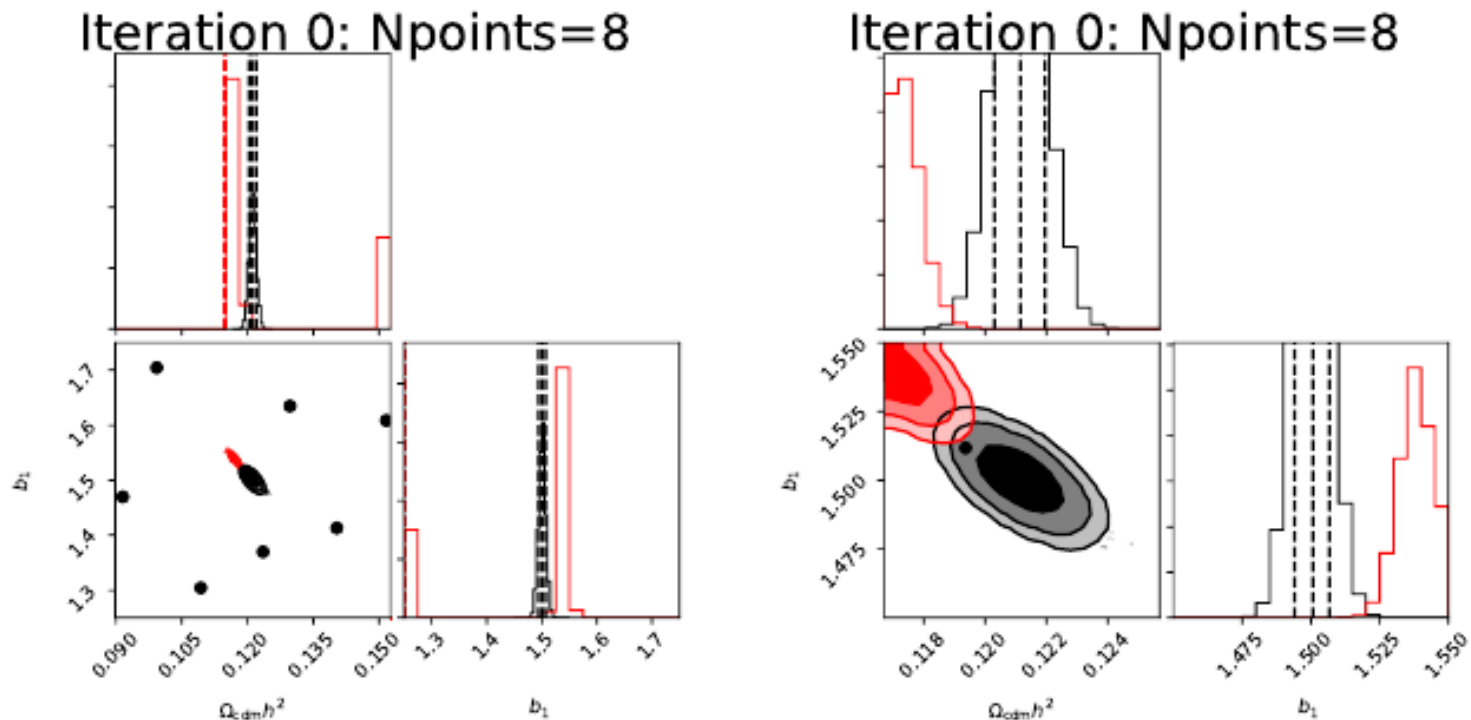
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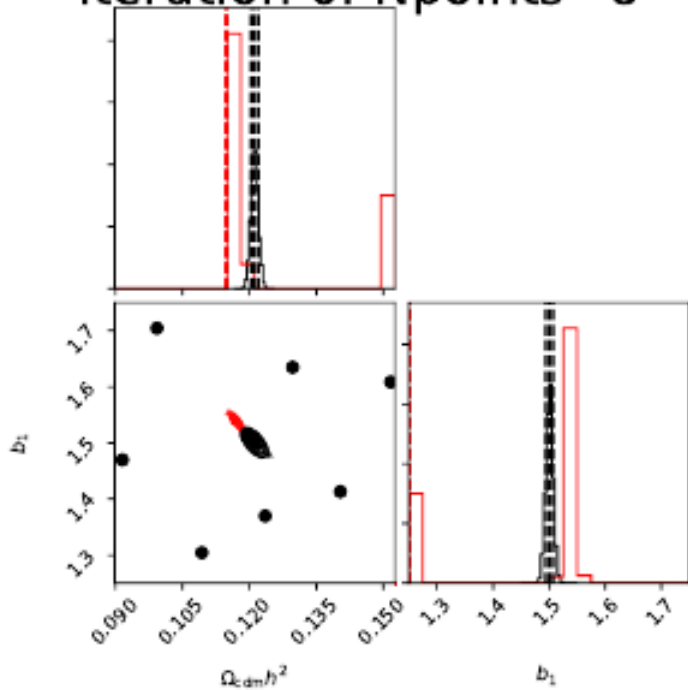


# Iterative process with Bayesian Optimization of Gaussian Process

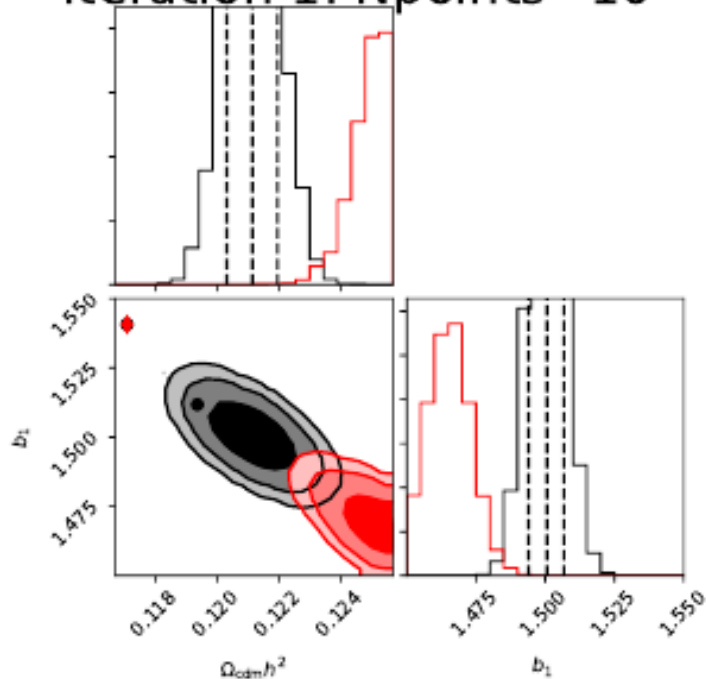


# Iterative process with Bayesian Optimization of Gaussian Process

Iteration 0: Npoints=8



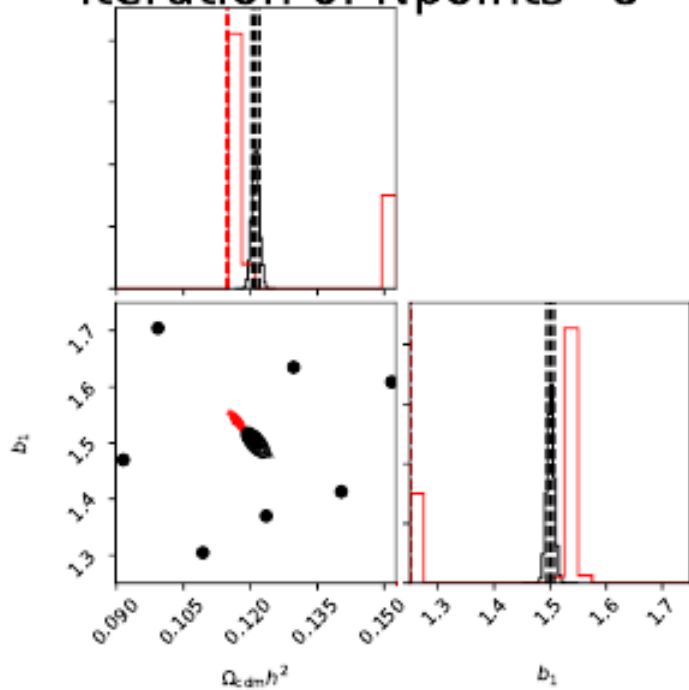
Iteration 1: Npoints=10



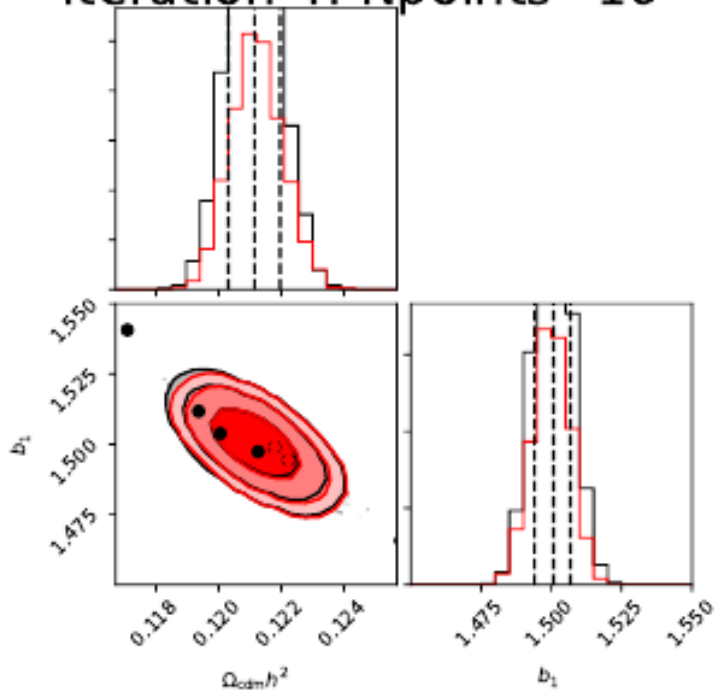
Pellejero-Ibanez, Arico, et al. (in prep.)

# Iterative process with Bayesian Optimization of Gaussian Process

Iteration 0: Npoints=8



Iteration 4: Npoints=16



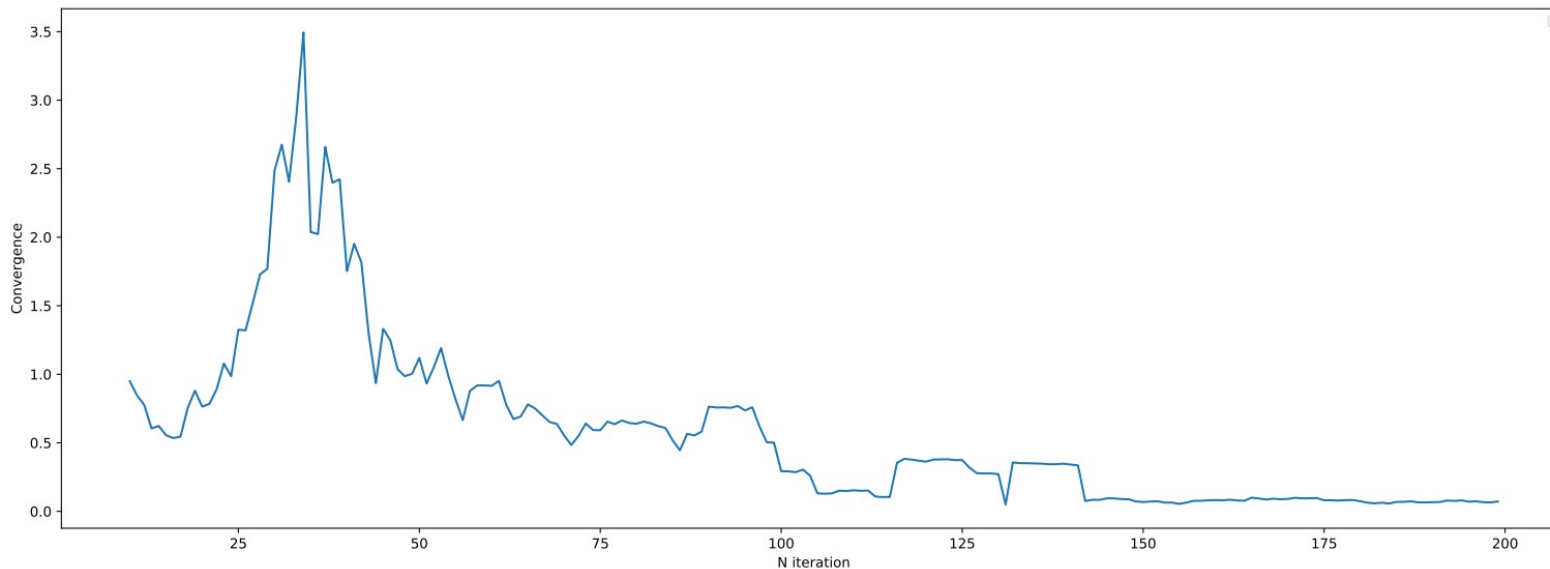
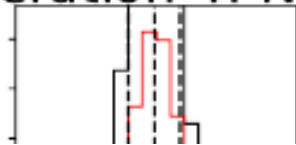
Pellejero-Ibanez, Arico, et al. (in prep.)

# Iterative process with Bayesian Optimization of Gaussian Process

Iteration 0: Npoints=8



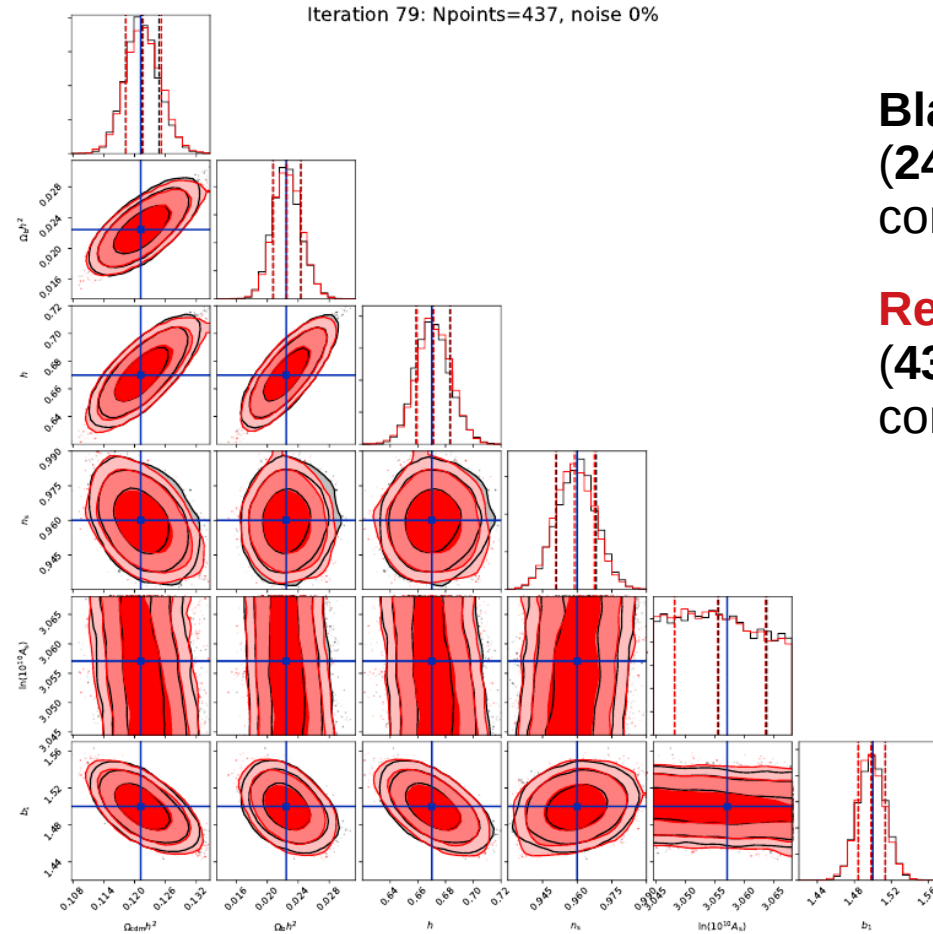
Iteration 4: Npoints=16



ez, Arico, et al. (in

prep.)

# In higher dimensions: clustering



**Black:** MCMC constraints  
(**24000** likelihood  
computations)

**Red:** Iterative constraints  
(**437** likelihood  
computations)

Pellejero-Ibanez, Arico, et al. (in prep.)



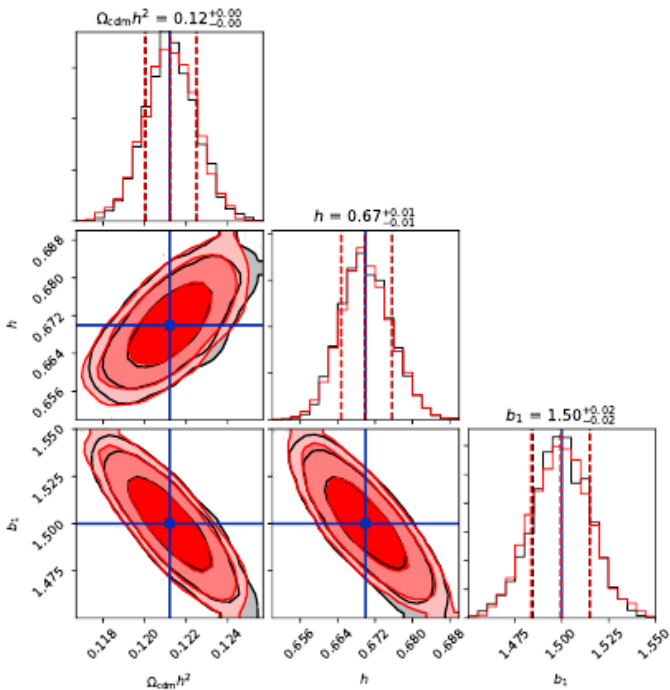
# Summary

- **Noisy likelihood**: Include **theory errors** and use **Gaussian Process** to recover “true” results.
- Use iterative **Bayesian Optimization process** to get minimal computations of the likelihood function.

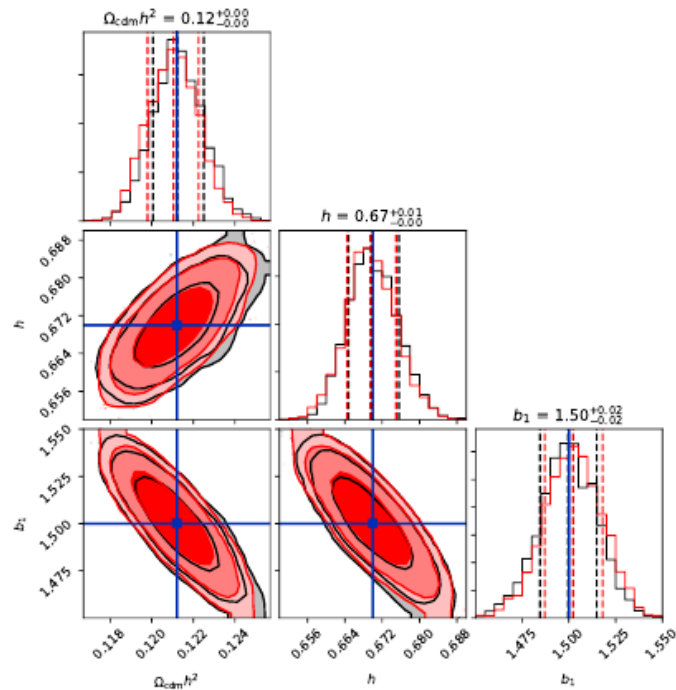
¡Muchas gracias!

# Appendix: Combining ideas

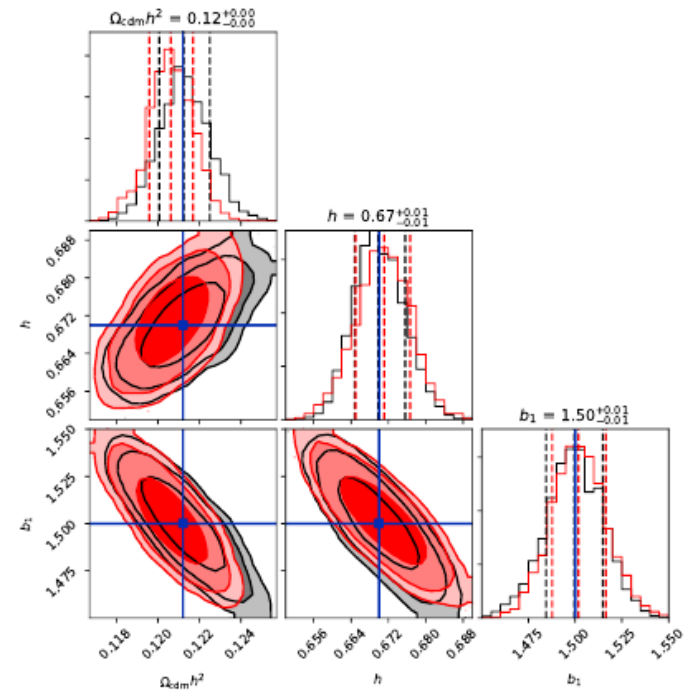
No noise



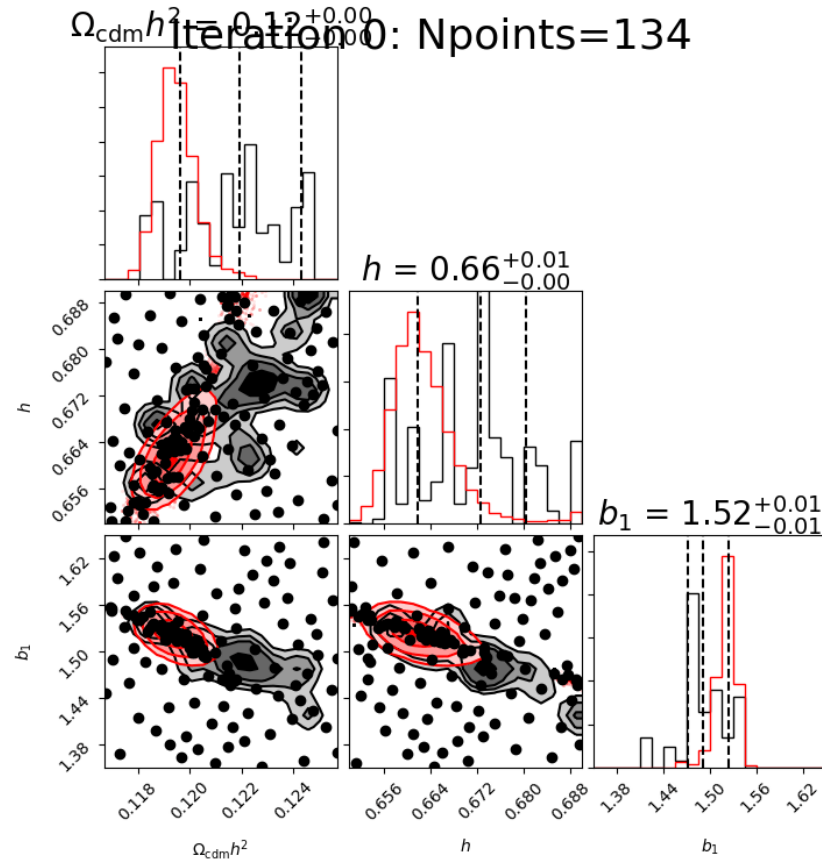
10% noise



50% noise

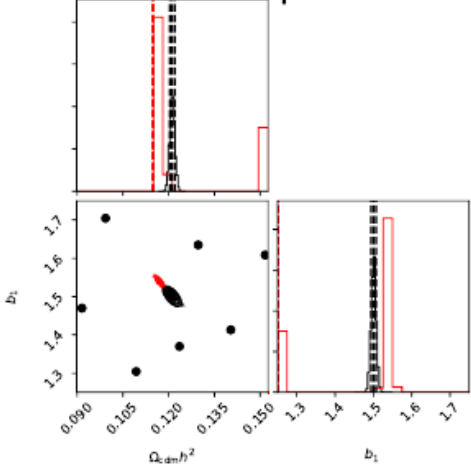


# Appendix: MCMC performance

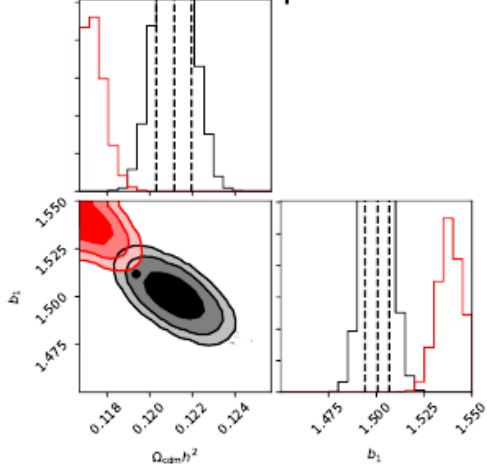


# Appendix: Iterative process with Bayesian Optimization of Gaussian Process

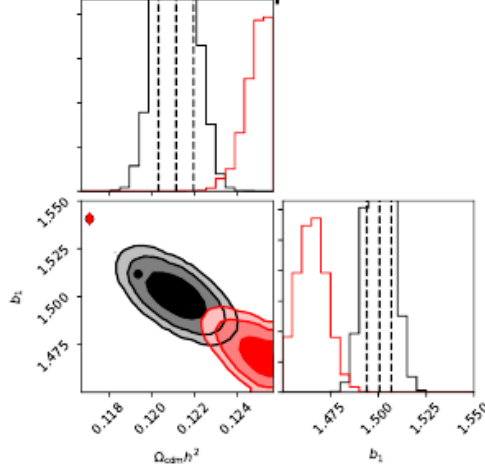
Iteration 0: Npoints=8



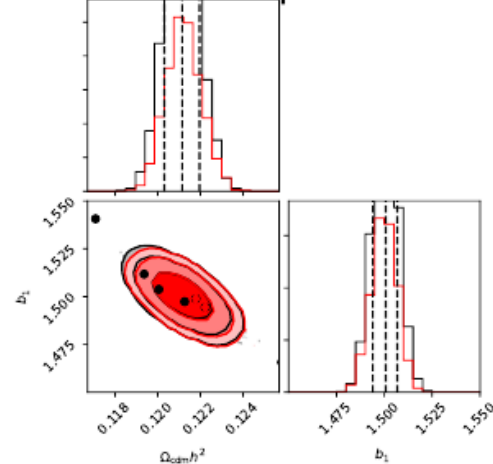
Iteration 0: Npoints=8



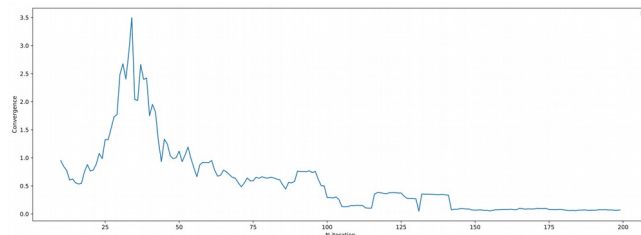
Iteration 1: Npoints=10



Iteration 4: Npoints=16

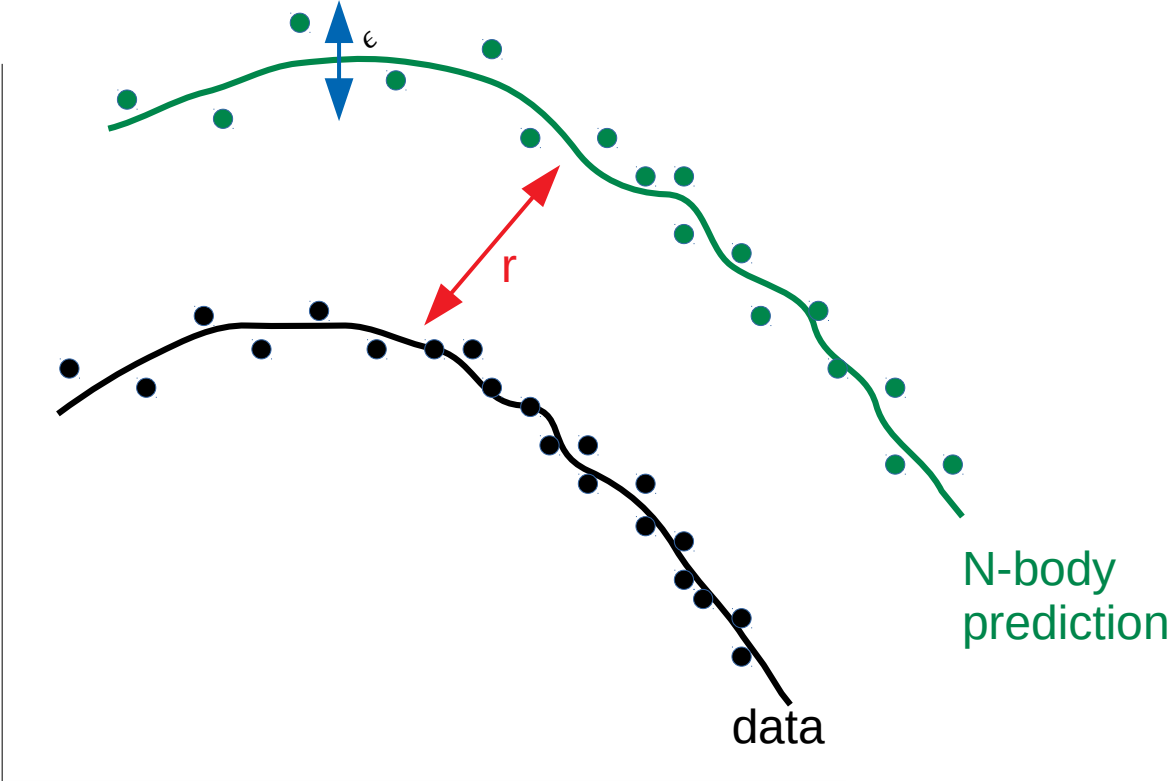


Convergence criteria



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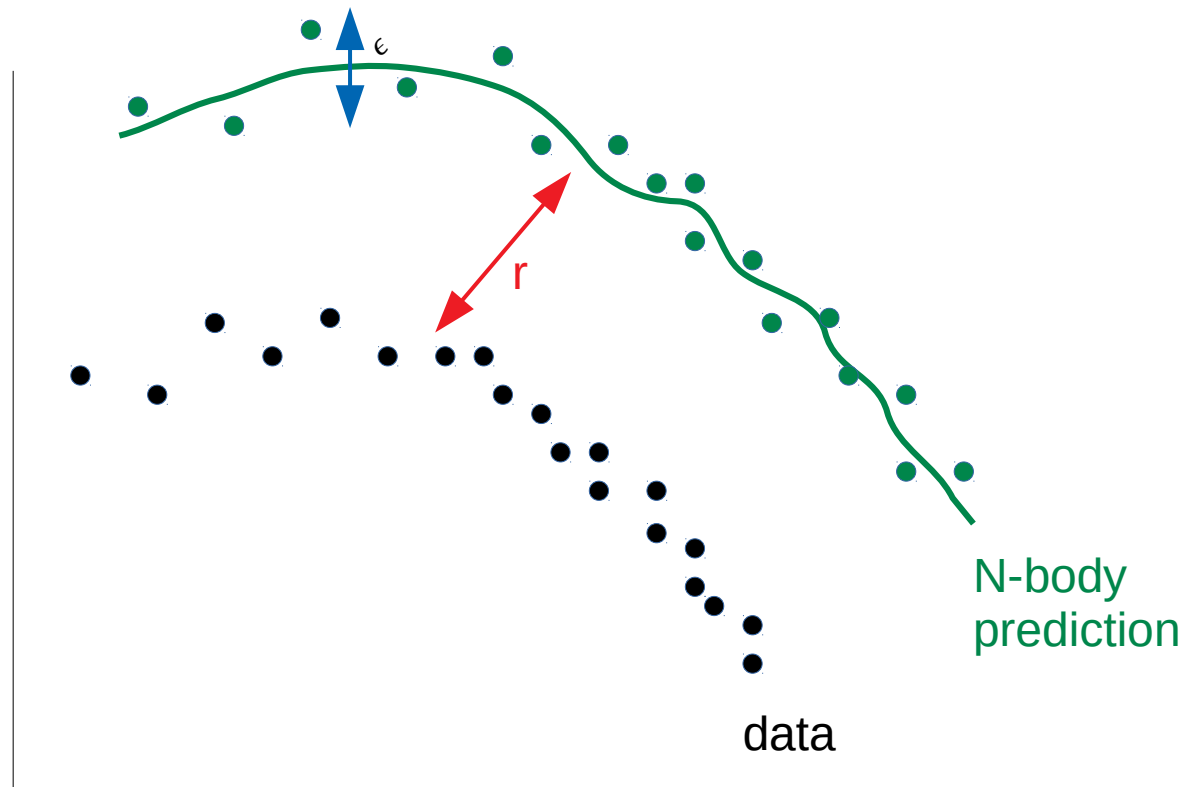
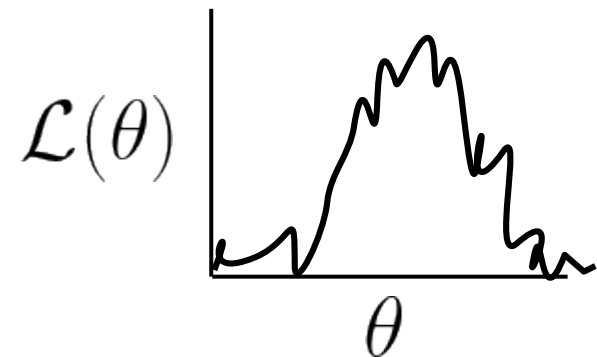
Appendix



# Simple example:

$$\epsilon = \epsilon(\theta)!!$$

Translates into noise  
in the likelihood.



# Simple example:

