

Inferring the Initial Condition for the Balitsky - Kovchegov Evolution Equation

Carlisle Casuga
in collaboration with M. Karhunen, H. Mäntysaari

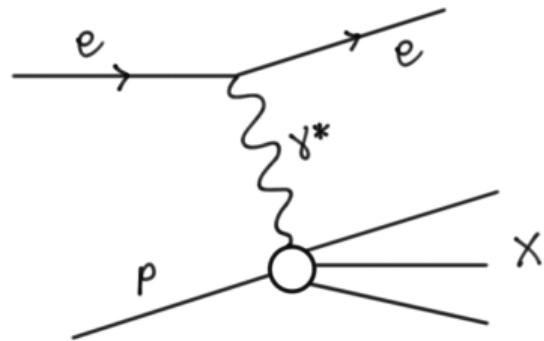
QCD theory group, University of Jyväskylä

Particle Physics Day, Oct 2023

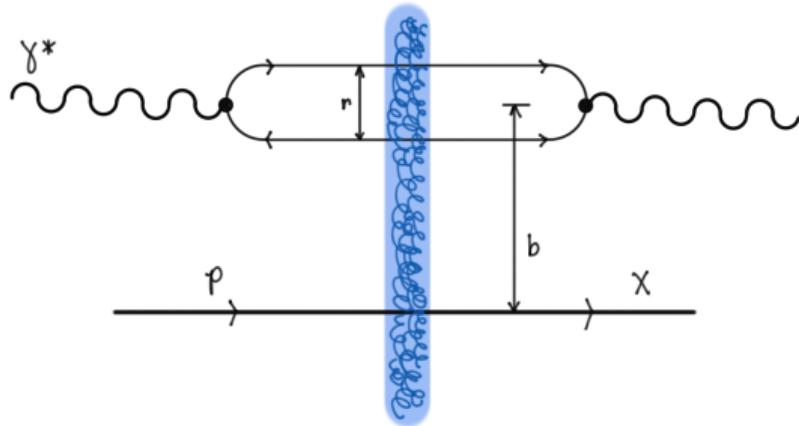


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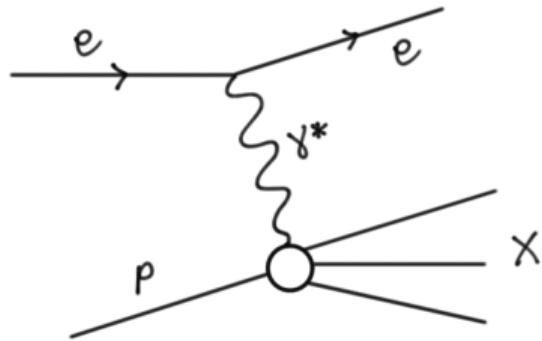
Deep Inelastic Scattering in the Dipole Picture



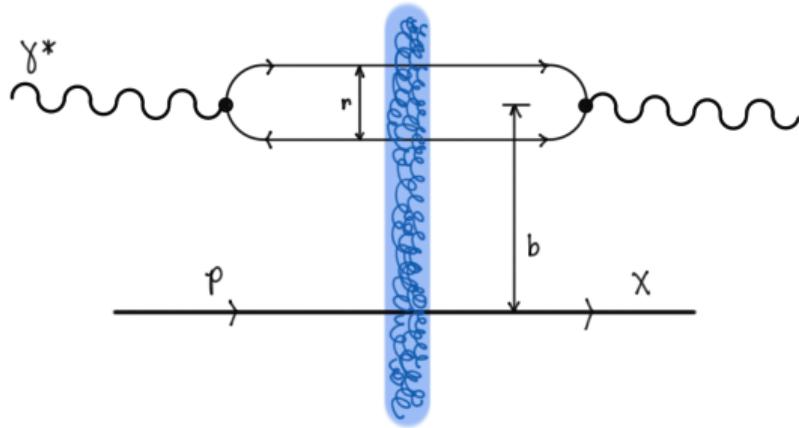
IMF picture



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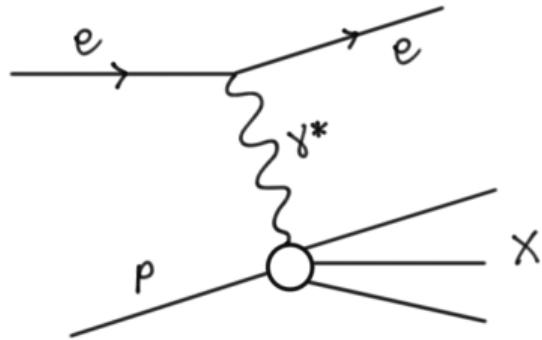
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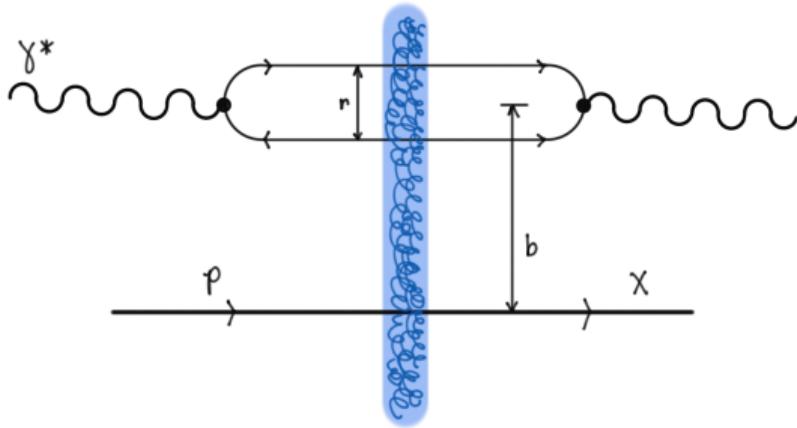
Dipole Picture

$$\sigma_{T,L}^{\gamma^* p}(x, Q^2) \sim \frac{\sigma_0}{2} \times \mathcal{N}(r, y) \times \{\text{LCWF}\}$$

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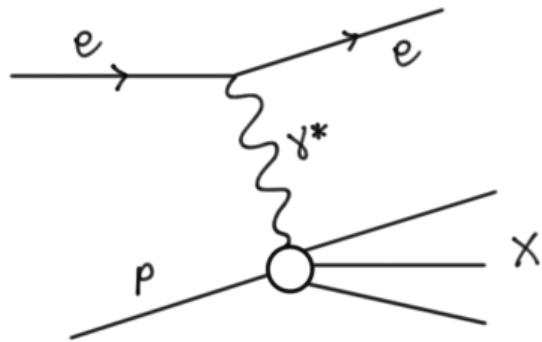


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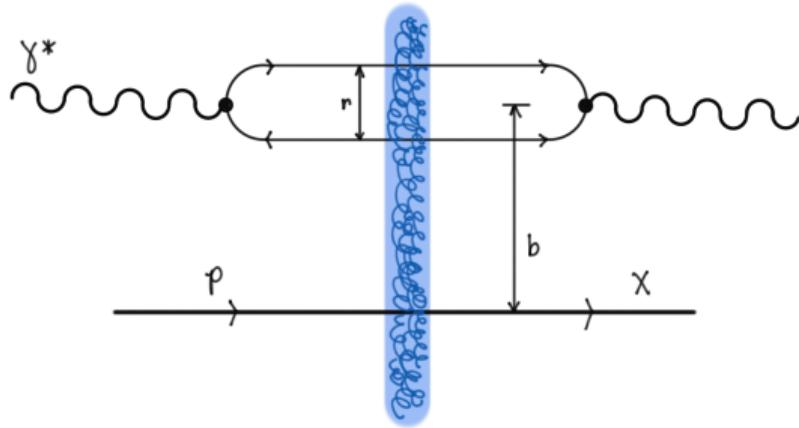
proton transverse size

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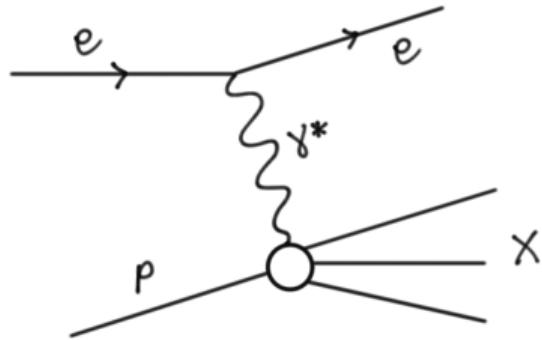
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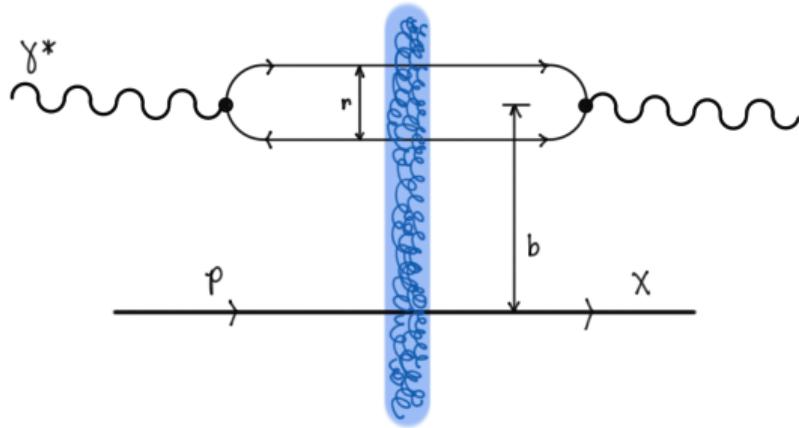
Dipole Picture

$$\sigma_{T,L}^{\gamma^* p}(x, Q^2) \sim \frac{\sigma_0}{2} \times \text{dipole-target scattering amplitude} \times \mathcal{N}(r, y) \times \{\text{LCWF}\}$$

Deep Inelastic Scattering in the Dipole Picture



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Dipole Picture

$$\sigma_{T,L}^{\gamma^* p}(x, Q^2) \sim \frac{\sigma_0}{2} \times \mathcal{N}(r, y) \times \{\text{LCWF}\}$$

$$\text{rcBK: } \mathcal{N}(r, x = x_0; Q_{s0}^2, \gamma, e_c) \xrightarrow{C^2} \mathcal{N}(r, y)$$

Objectives

- Constrain model parameters, $[Q_{s0}^2, \gamma, e_c, C^2, \sigma_0/2]$, that parametrize the BK IC ...
 - ... via Bayesian inference using HERA structure function data.
- Account for correlated experimental uncertainties in HERA data.
- Provide predictions and uncertainties for other observables.

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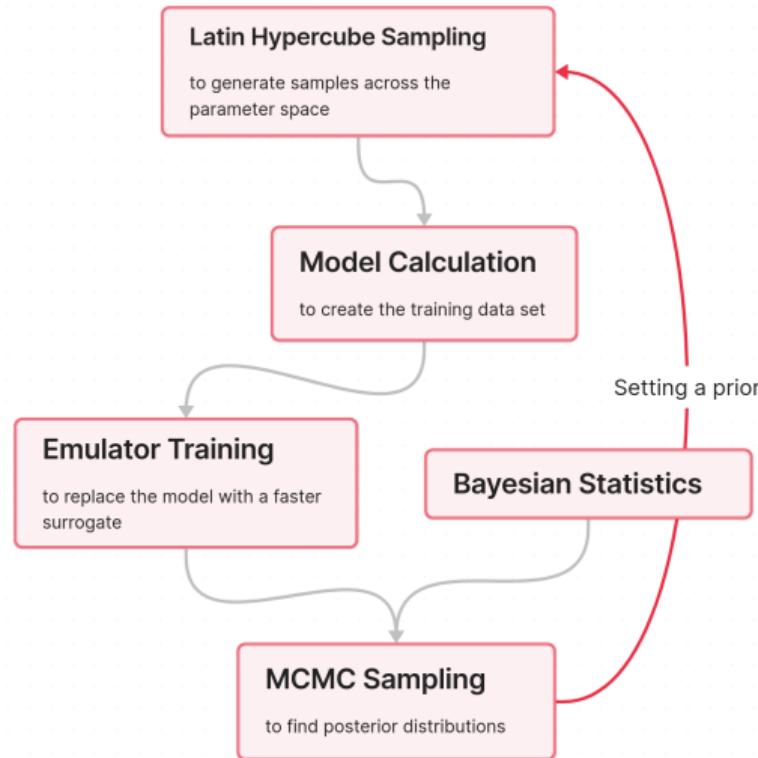
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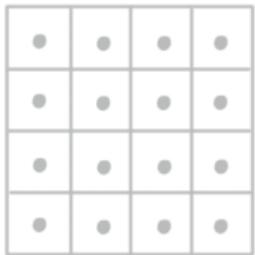
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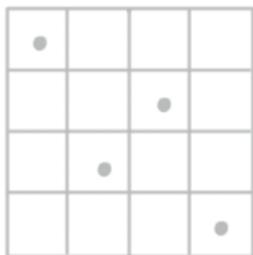
Typical Bayesian Workflow



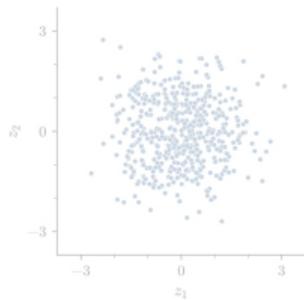
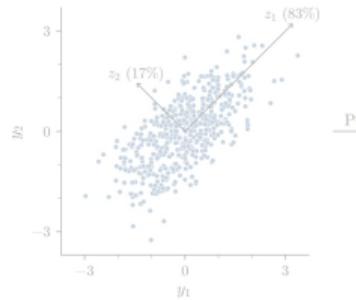
Latin Hypercube Sampling



VA

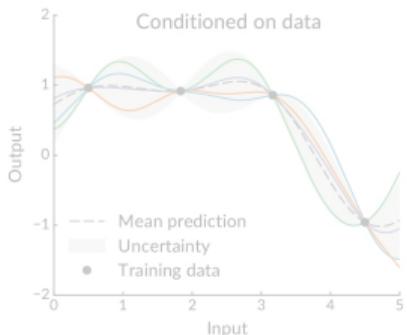


Principal Component Analysis

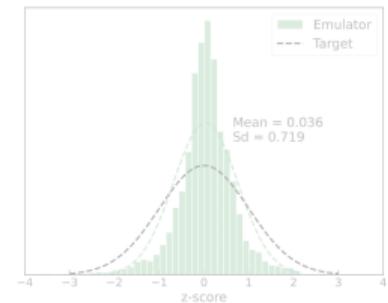
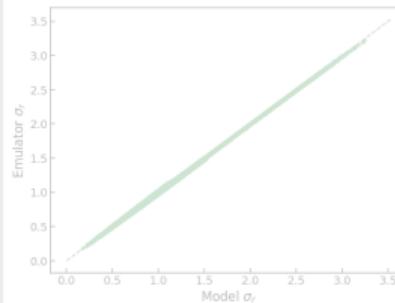


Gaussian Process Emulator

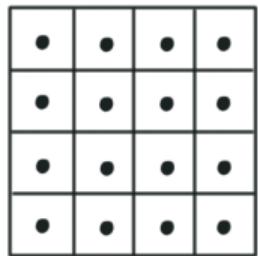
GPs learn the parameter dependence of the model!



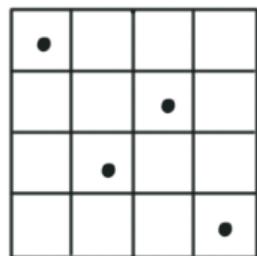
Validation



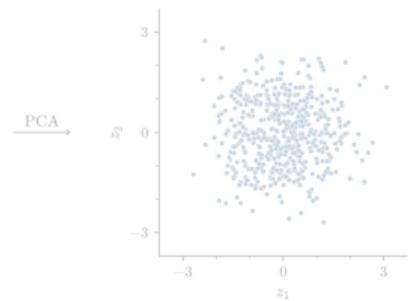
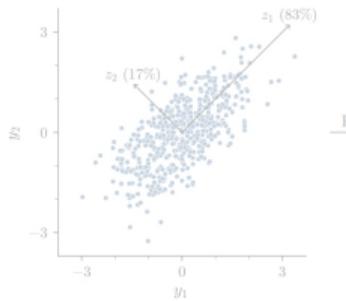
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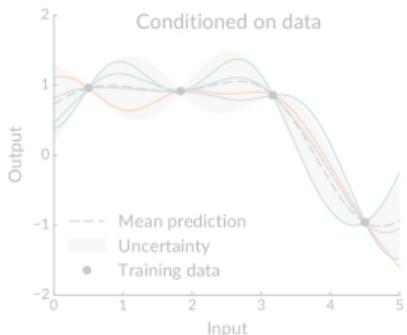


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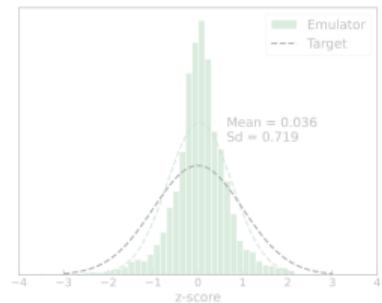
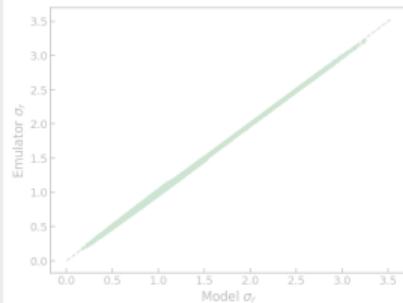


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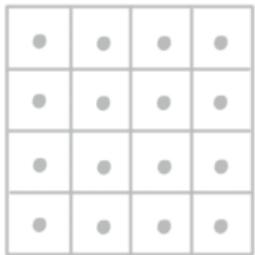
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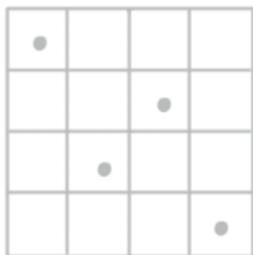
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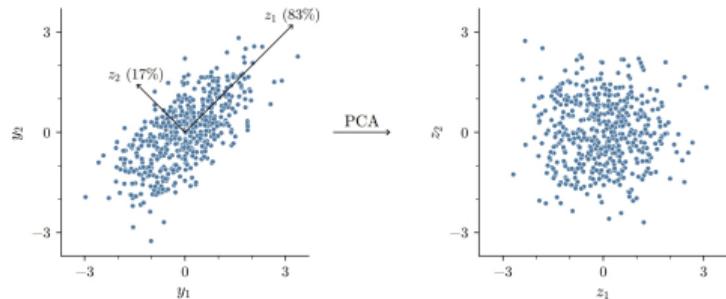
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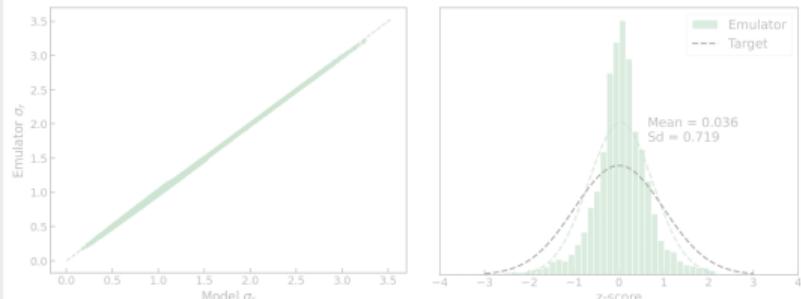


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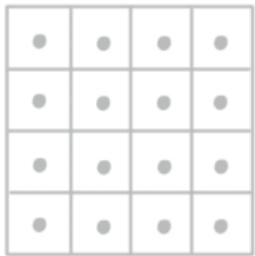
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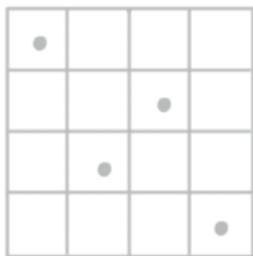
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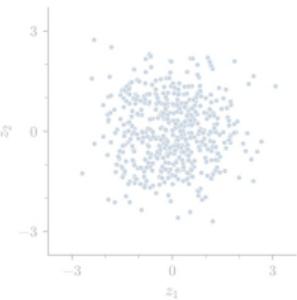
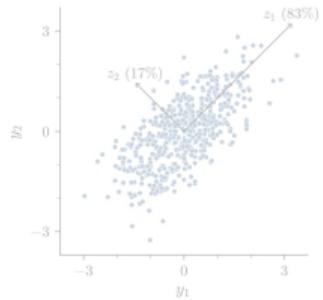
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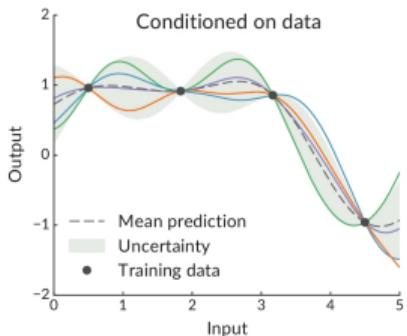


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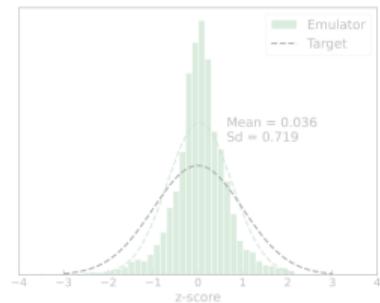
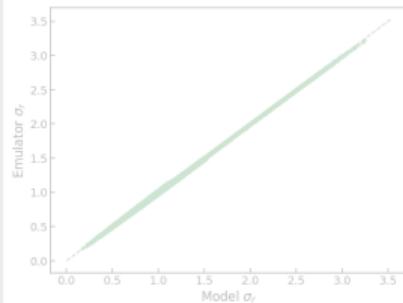


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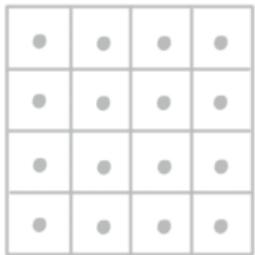
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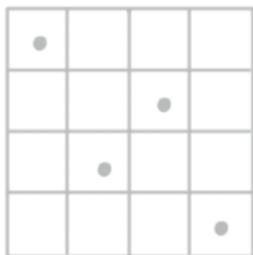
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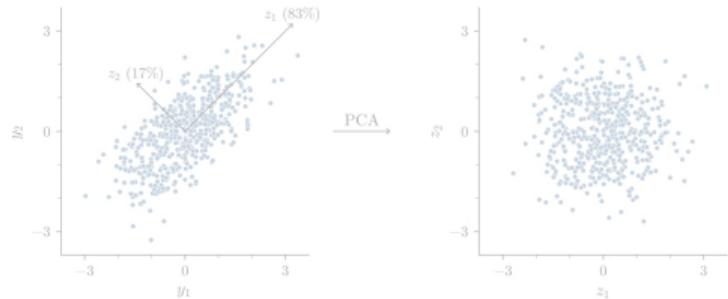
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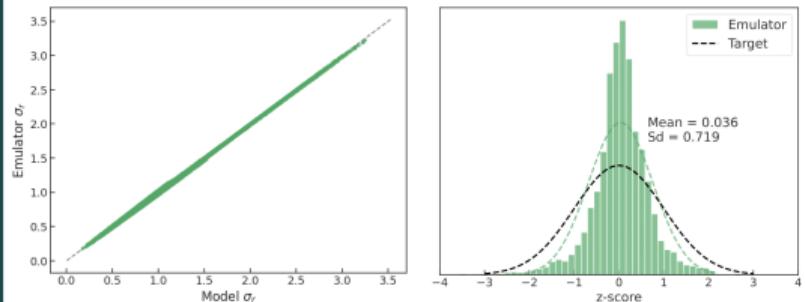


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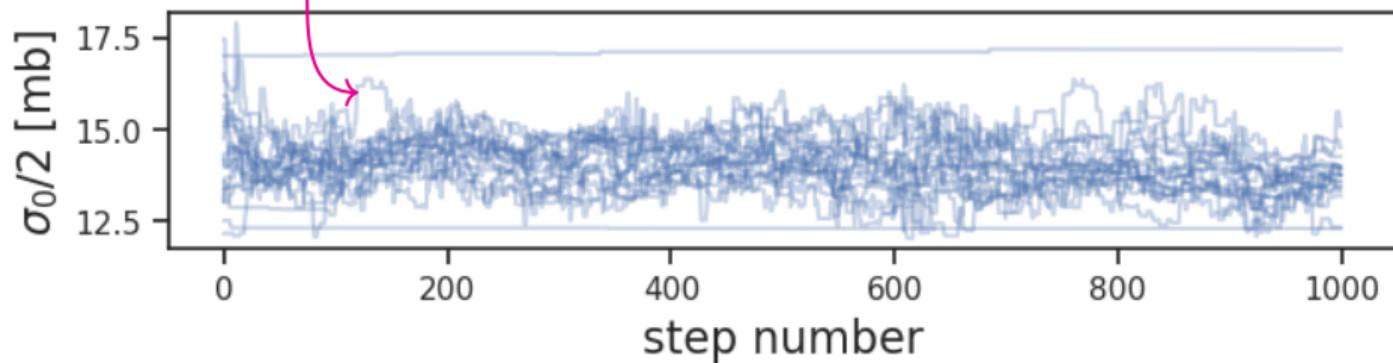


Validation



Acceptance probability:

$$\alpha = \frac{P(\theta_{x+1})}{P(\theta_x)}$$



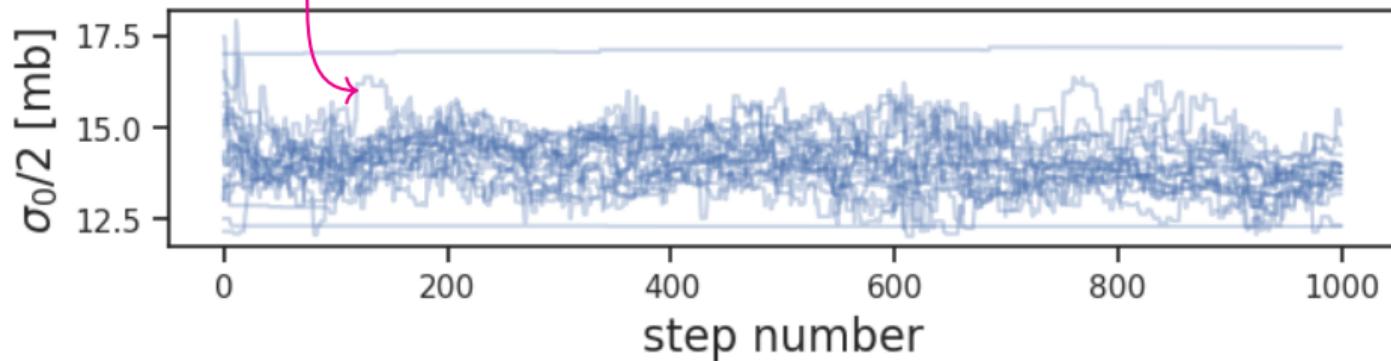
Bayesian Statistics

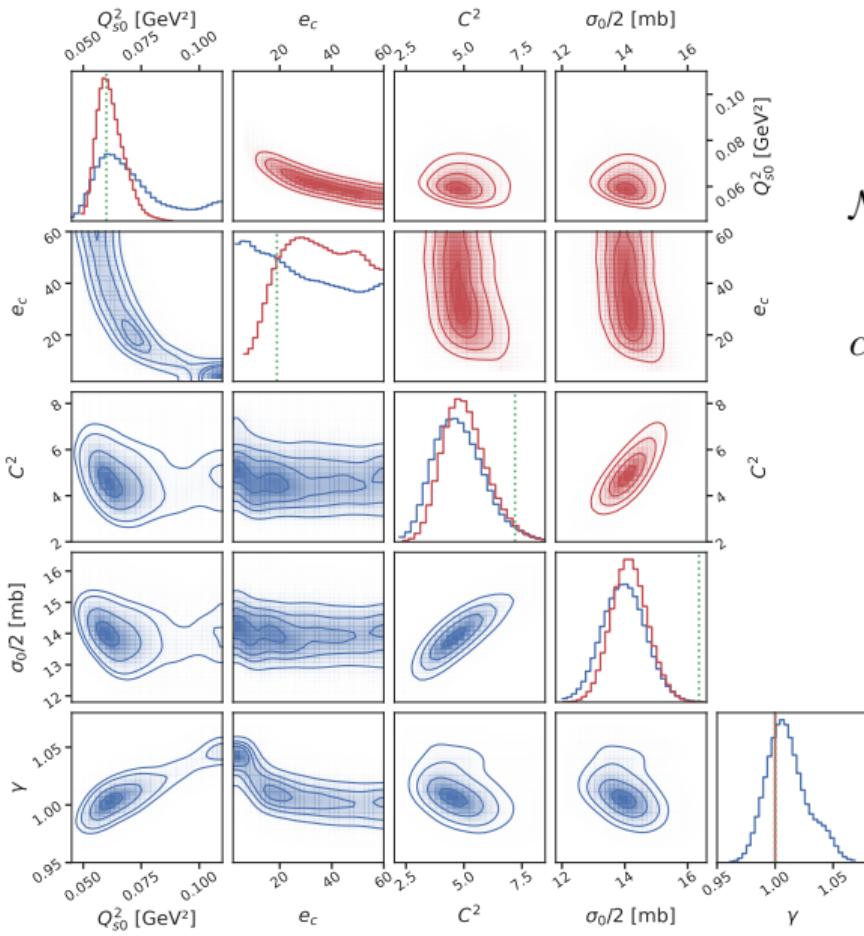
$$P(\theta) = \text{posterior} = \text{likelihood} \times \text{prior}$$

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$$\alpha = \frac{P(\theta_{x+1})}{P(\theta_x)}$$

- Likelihood: how well data matches the model at θ
- Prior: bounds of the parameter space



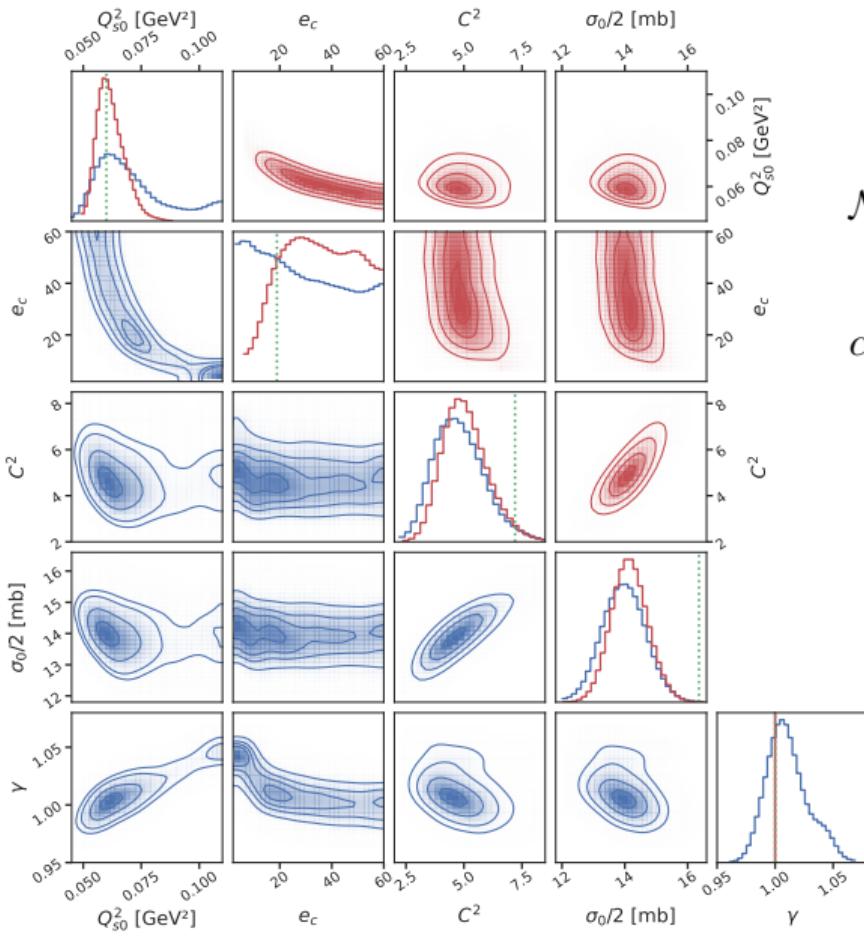


Results: Posterior Distribution

$$\mathcal{N}(\mathbf{r}, \mathbf{x}_0) = 1 - \exp \left[-\frac{(\mathbf{r}^2 Q_{s0}^2)^\gamma}{4} \ln \left(\frac{1}{|\mathbf{r}| \Lambda_{QCD}} + \mathbf{e}_c \cdot \mathbf{e} \right) \right]$$

$$\alpha_s(\mathbf{r}) = \frac{12\pi}{(33 - N_f) \log \left(\frac{4C^2}{\mathbf{r}^2 \Lambda_{QCD}^2} \right)}$$

- 1 HERA data prefers a $\gamma \approx 1$
- 2 With γ as a free parameter, we allow a wider posterior distribution
- 3 Off-diagonal plots = correlations

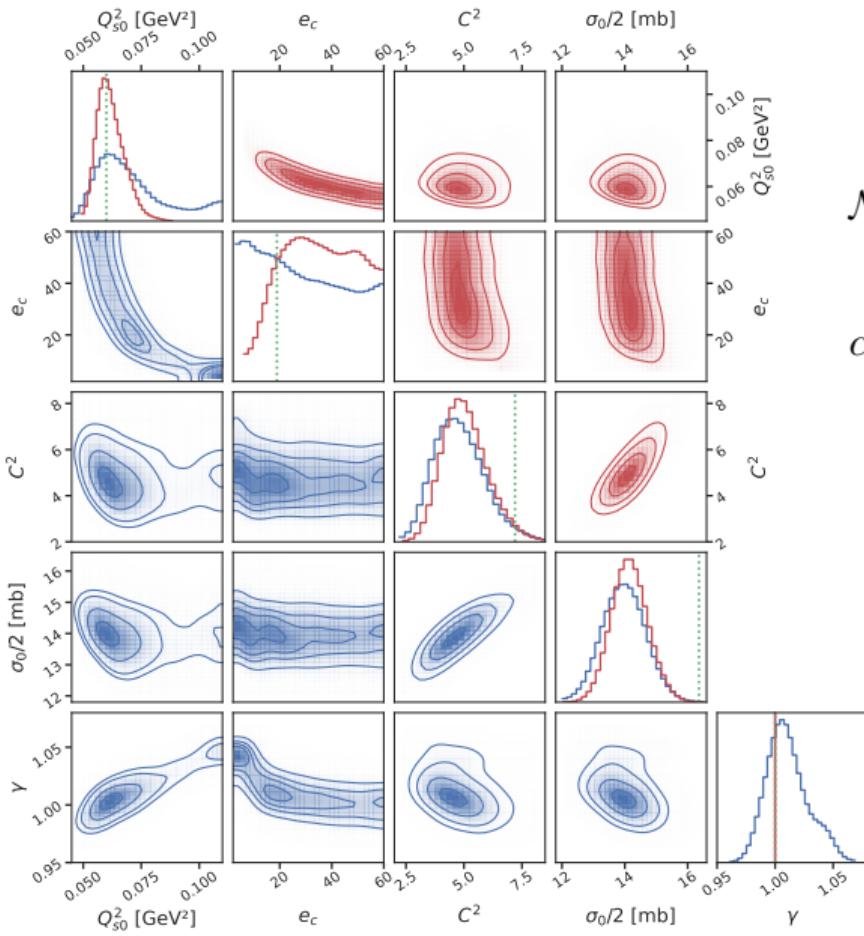


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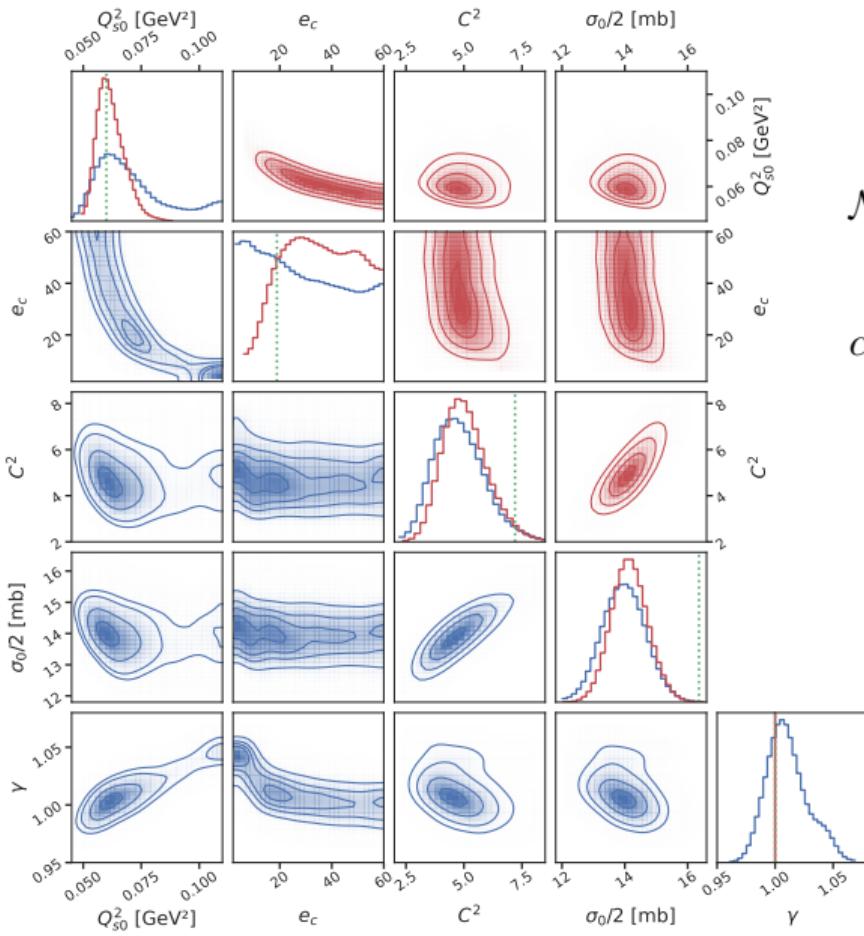


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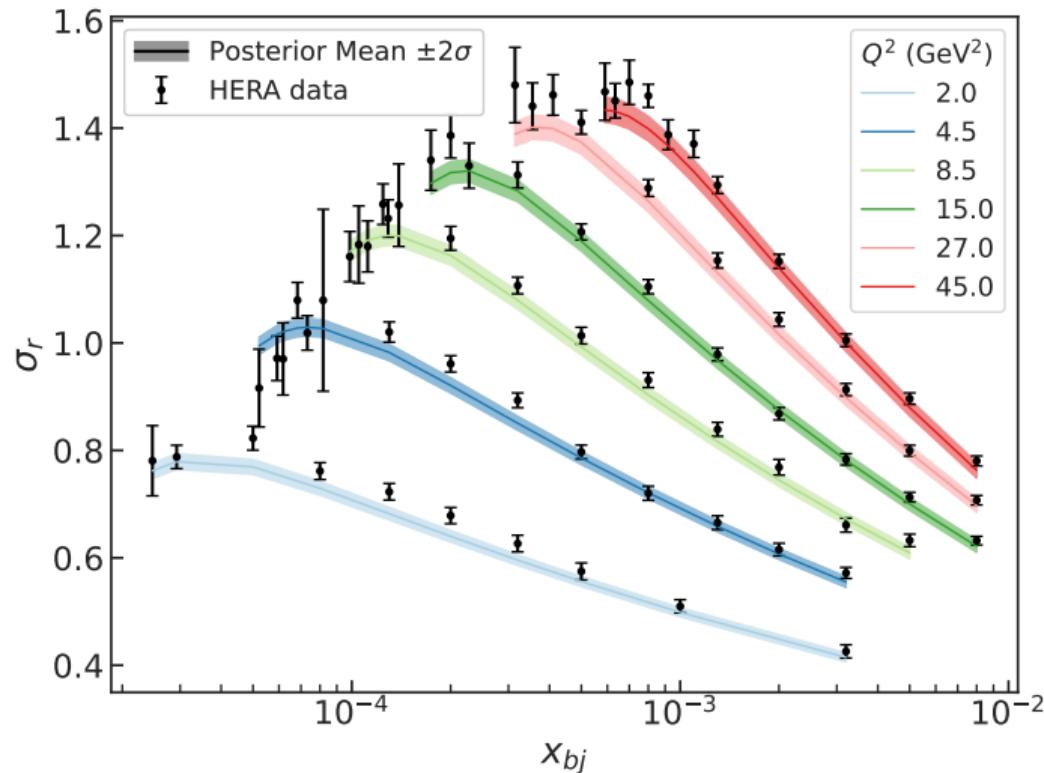
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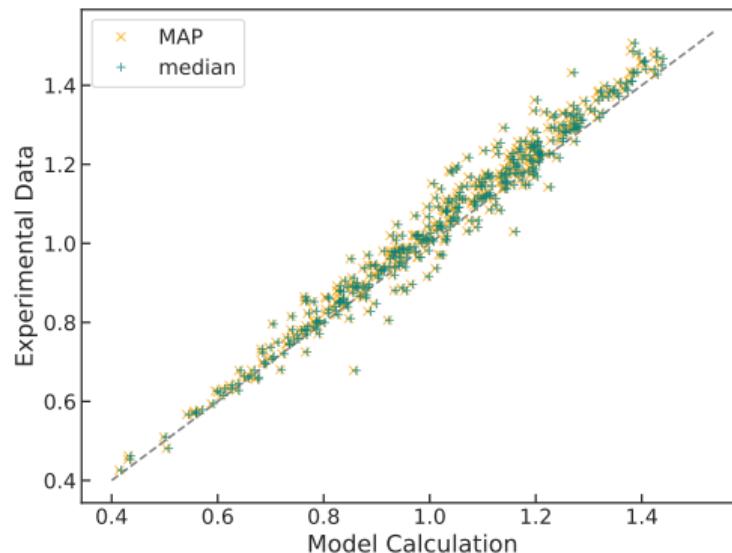
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Posterior Samples, Median and MAP curves



“Best Fit” Values

5 - parameter	$Q_{s0}^2[\text{GeV}^2]$	γ	e_c	C^2	$\sigma_0/2[\text{mb}]$	χ^2/dof
median	0.067	1.01	27.5	4.72	14.0	1.63
MAP	0.076	1.01	15.6	4.47	13.9	2.06



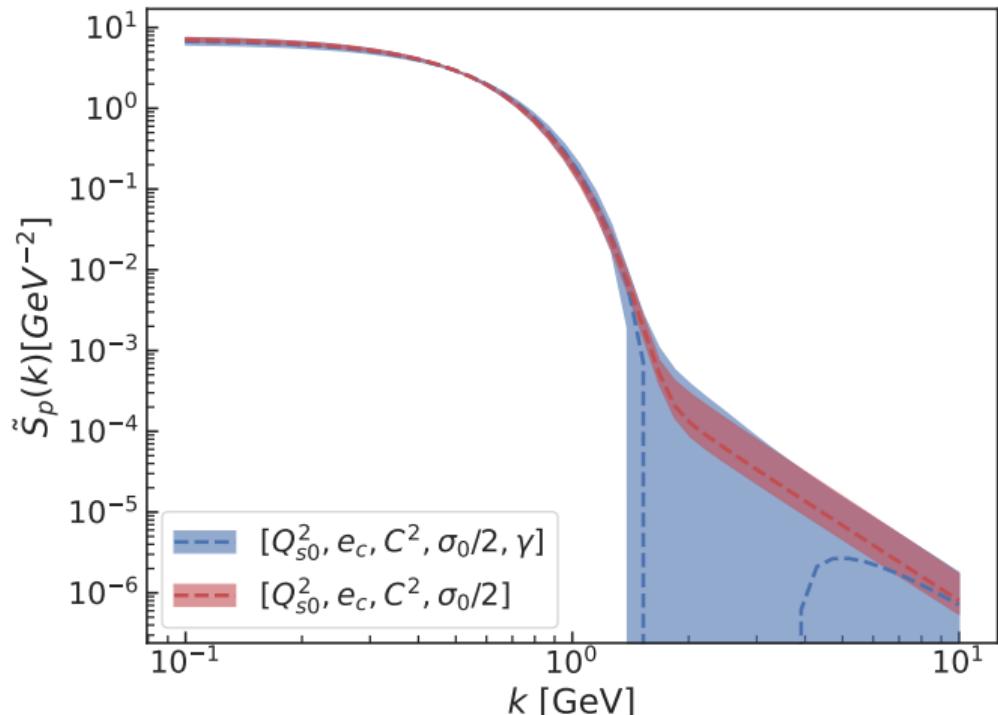
Applications to pA collisions

$$d\sigma^{q+A \rightarrow q+X} = xg(x, \mathbf{k}^2) \tilde{S}_p(\mathbf{k})$$

$\tilde{S}_p(\mathbf{k}) \rightarrow$ 2DFT of Dipole amplitude

$$= \int d^2\mathbf{r} e^{i\mathbf{k}\cdot\mathbf{r}} \\ \times [1 - \mathcal{N}(\mathbf{r}, x = x_0)]$$

- $\gamma > 1$ result to negative 2DFT values $\Rightarrow \sigma/k^2 < 0$
- Uncertainty estimates are now provided!



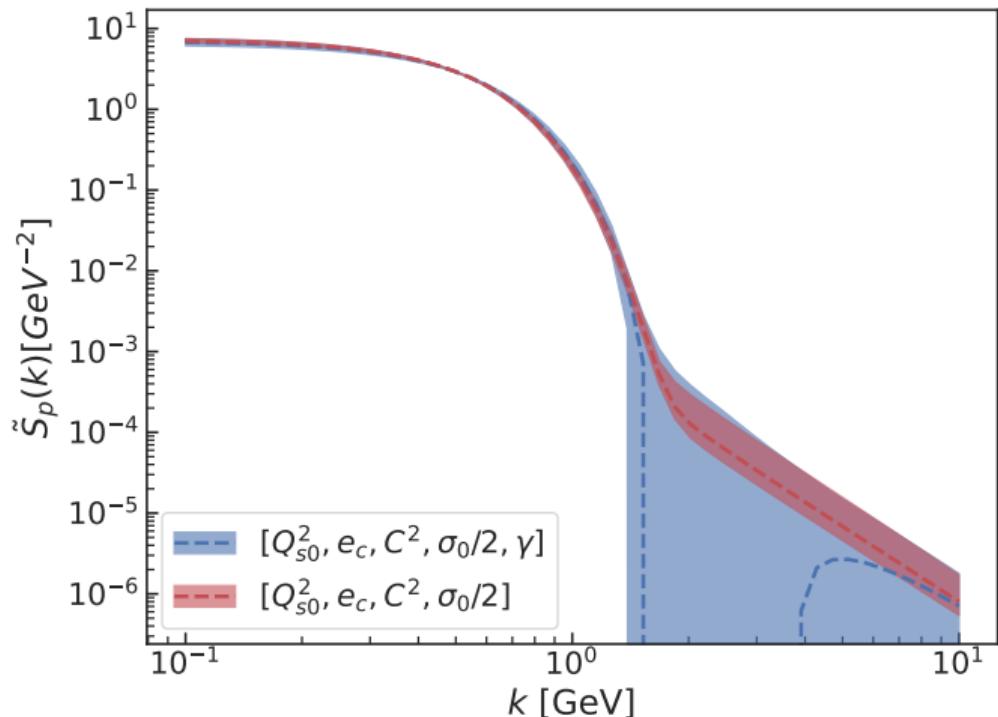
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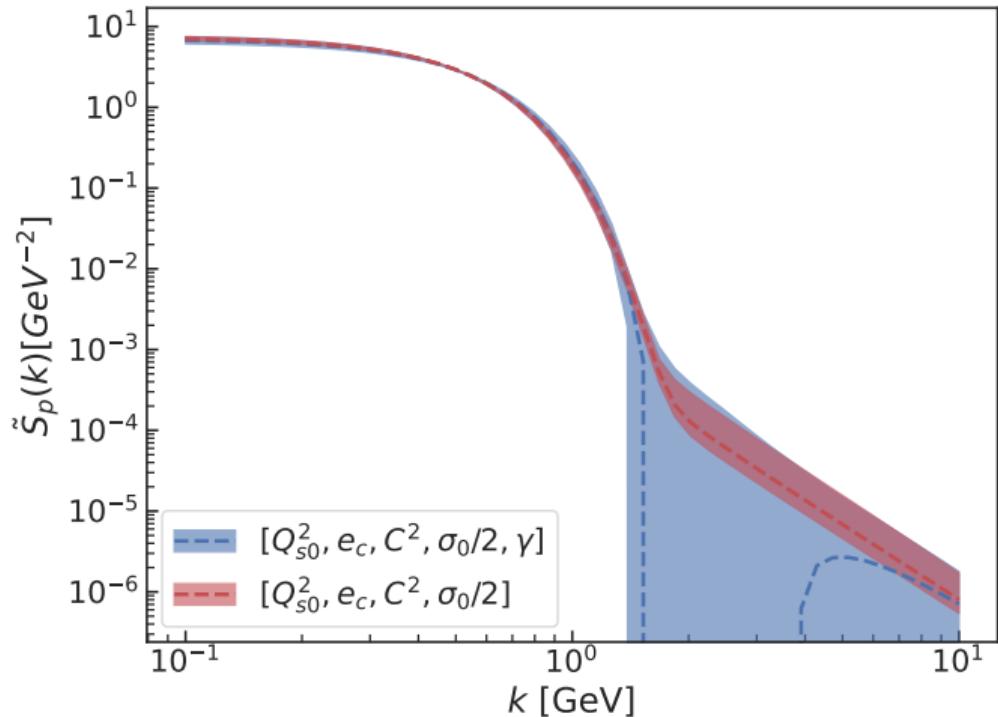
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Summary

- Posterior distribution for $[Q_{s0}^2, \gamma, e_c, C^2, \sigma_0/2]$
- Correlations between parameters observed from the posteriors
- Uncertainty for the BK initial condition (novel!)
- necessary for calculations that propagate the uncertainties of non-perturbative BK IC and other observables

Further work

- Extension to other functional forms of the initial condition
- NLO fits to further probe saturation

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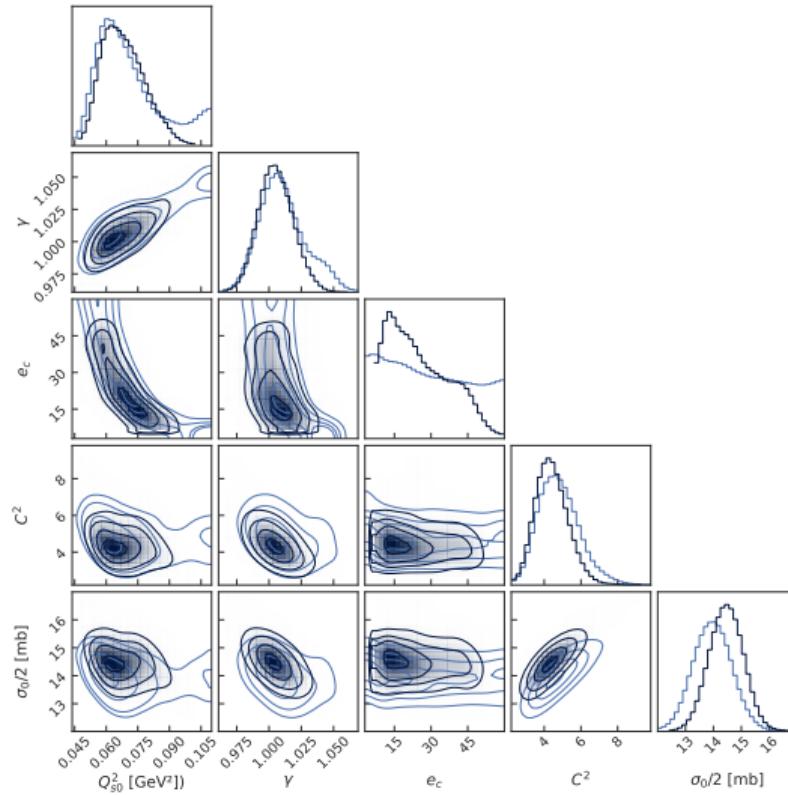
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Back up Slides

Correlations



Initial and Evolved $\mathcal{N}(r, y)$

