

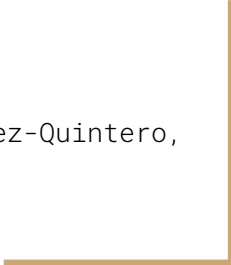


# Reconstructing QCD Spectral Functions with Gaussian Processes

arXiv:2107.13464\*

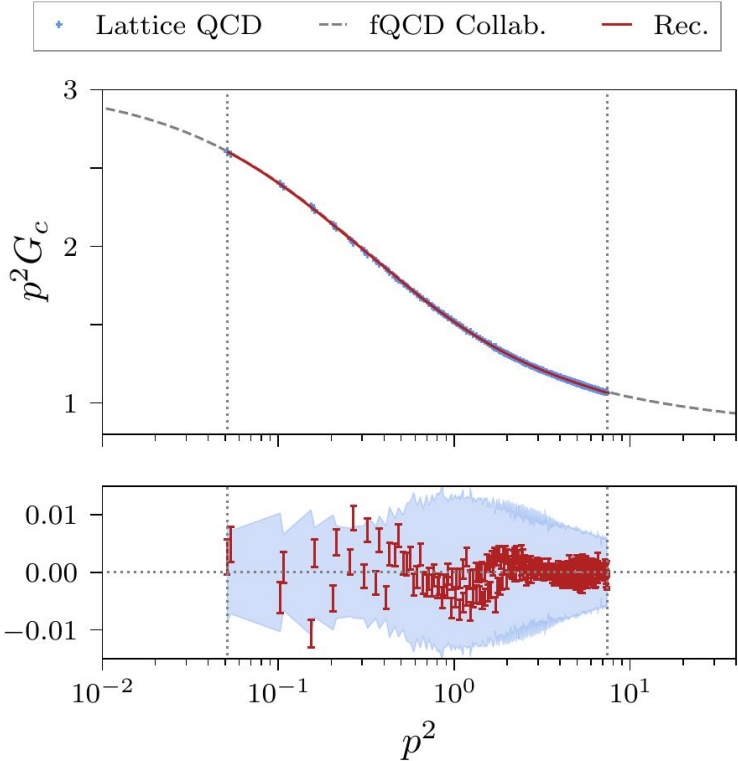
Julian Urban  
ITP Heidelberg

\*in collaboration with Jan Horak, Jan M. Pawłowski, José Rodríguez-Quintero,  
Jonas Turnwald, Nicolas Wink, Savvas Zafeiropoulos

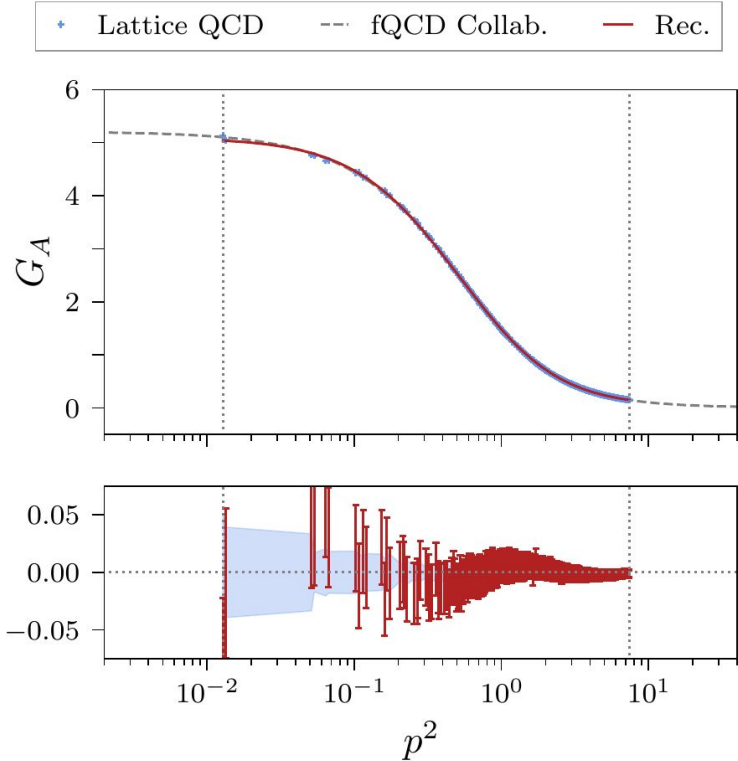


# Results Teaser

## Ghost



## Gluon



# Motivation

- Imaginary-time accessible via lattice and functional methods
- Real-time properties still notoriously difficult
- Applications
  - Hadronic resonance spectrum
  - Scattering processes
  - Transport & non-equilibrium phenomena in heavy-ion collisions

→ From Euclidean to Minkowski  
via spectral reconstruction

# Spectral Functions

- Spectral representation of two-point correlators

$$G(p_0) = \int_0^\infty \frac{d\omega}{\pi} \frac{\omega \rho(\omega)}{\omega^2 + p_0^2} = \int_0^\infty d\omega K(p_0, \omega) \rho(\omega)$$

$$\rho(\omega) = 2 \operatorname{Im} G(-i(\omega + i0^+))$$

- Properties of the spectral function

- Vanishing spectral weight:  $\int_0^\infty \frac{d\omega}{\pi} \omega \rho_{A/c}(\omega) = 0$

- Decomposition into resonance peaks and continuous part:

$$\rho_c(\omega) = \frac{\pi}{Z_c} \frac{\delta(\omega)}{\omega} + \tilde{\rho}_c(\omega), \quad \int_0^\infty \frac{d\omega}{\pi} \omega \tilde{\rho}_c(\omega) = -\frac{1}{Z_c}$$

# Gaussian Process Regression

- GP describes distribution over functions

$$\rho(\omega) \sim \mathcal{GP}(\mu(\omega), C(\omega, \omega'))$$

- Multivariate Gaussian distribution for evaluation at specific nodes

$$\begin{pmatrix} \rho(\omega_1) \\ \vdots \\ \rho(\omega_N) \end{pmatrix} \sim \mathcal{N} \left( \begin{pmatrix} \mu(\omega_1) \\ \vdots \\ \mu(\omega_N) \end{pmatrix}, \begin{pmatrix} C(\omega_1, \omega_1) & \dots & C(\omega_1, \omega_N) \\ \vdots & \ddots & \vdots \\ C(\omega_N, \omega_1) & \dots & C(\omega_N, \omega_N) \end{pmatrix} \right)$$

- Joint distribution of observations and predictions

$$\begin{pmatrix} \rho(\omega) \\ \hat{\rho} \end{pmatrix} \sim \mathcal{N} \left( \begin{pmatrix} \mu(\omega) \\ \hat{\mu} \end{pmatrix}, \begin{pmatrix} C(\omega, \omega) & \hat{\mathbf{C}}^T(\omega) \\ \hat{\mathbf{C}}(\omega) & \hat{\mathbf{C}} + \sigma_n^2 \cdot \mathbf{1} \end{pmatrix} \right)$$

$$\hat{\mu} \equiv \mu(\hat{\omega}_i), \hat{\mathbf{C}}_i(\omega) \equiv C(\hat{\omega}_i, \omega), \hat{\mathbf{C}}_{ij} \equiv C(\hat{\omega}_i, \hat{\omega}_j)$$

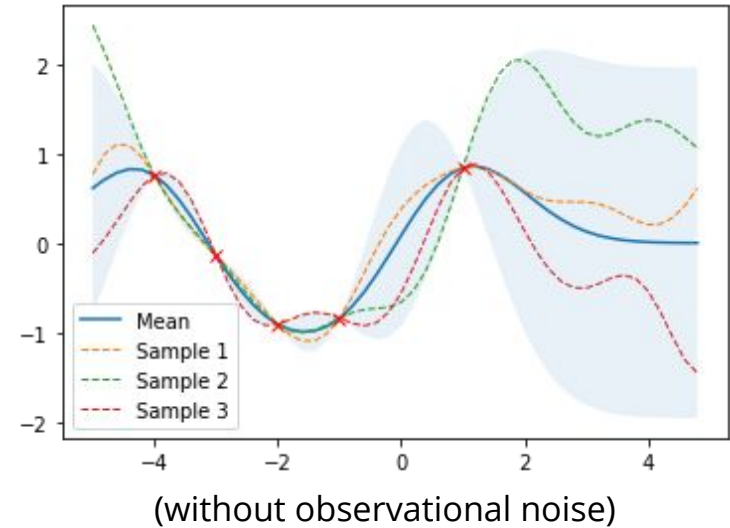
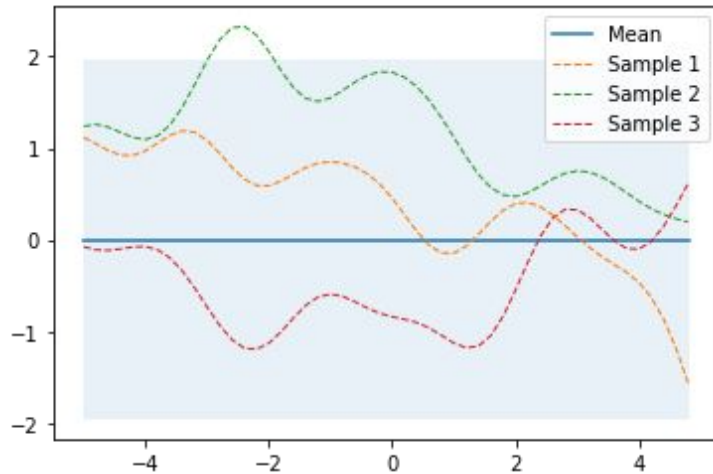
- Conditional distribution of predictions given observations

$$\rho(\omega) | \hat{\rho} \sim \mathcal{N} \left( \mu(\omega) + \hat{\mathbf{C}}^T(\omega) \left( \hat{\mathbf{C}} + \sigma_n^2 \cdot \mathbf{1} \right)^{-1} (\hat{\rho} - \hat{\mu}), C(\omega, \omega) - \hat{\mathbf{C}}^T(\omega) \left( \hat{\mathbf{C}} + \sigma_n^2 \cdot \mathbf{1} \right)^{-1} \hat{\mathbf{C}}(\omega) \right)$$

# Gaussian Process Regression

$$\rho(\omega) \sim \mathcal{GP}(\mu(\omega), C(\omega, \omega'))$$

$$\rho(\omega) | \hat{\rho} \sim \mathcal{N} \left( \mu(\omega) + \hat{\mathbf{C}}^T(\omega) \left( \hat{\mathbf{C}} + \sigma_n^2 \cdot \mathbf{1} \right)^{-1} (\hat{\rho} - \hat{\mu}), \right. \\ \left. C(\omega, \omega) - \hat{\mathbf{C}}^T(\omega) \left( \hat{\mathbf{C}} + \sigma_n^2 \cdot \mathbf{1} \right)^{-1} \hat{\mathbf{C}}(\omega) \right)$$

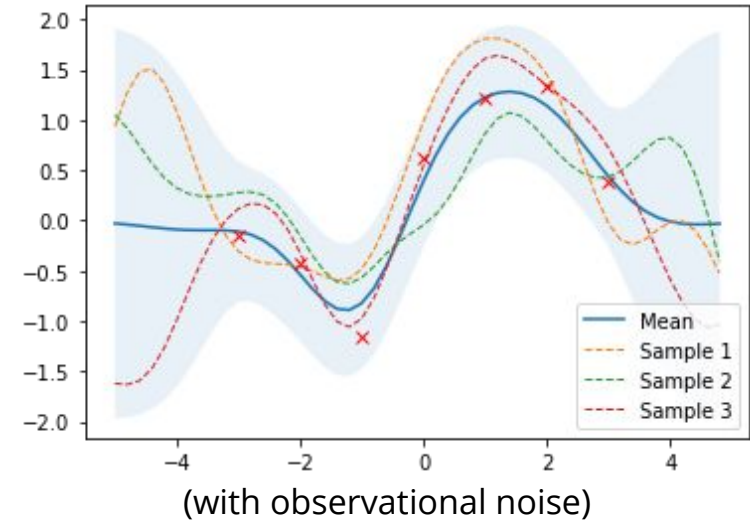
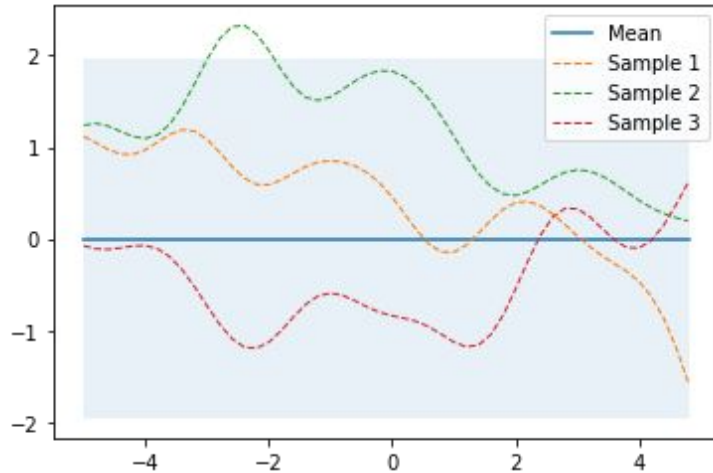


[krasserm.github.io/2018/03/19/gaussian-processes/](https://krasserm.github.io/2018/03/19/gaussian-processes/)

# Gaussian Process Regression

$$\rho(\omega) \sim \mathcal{GP}(\mu(\omega), C(\omega, \omega'))$$

$$\rho(\omega) | \hat{\rho} \sim \mathcal{N} \left( \mu(\omega) + \hat{\mathbf{C}}^T(\omega) \left( \hat{\mathbf{C}} + \sigma_n^2 \cdot \mathbf{1} \right)^{-1} (\hat{\rho} - \hat{\mu}), \right. \\ \left. C(\omega, \omega) - \hat{\mathbf{C}}^T(\omega) \left( \hat{\mathbf{C}} + \sigma_n^2 \cdot \mathbf{1} \right)^{-1} \hat{\mathbf{C}}(\omega) \right)$$



[krasserm.github.io/2018/03/19/gaussian-processes/](https://krasserm.github.io/2018/03/19/gaussian-processes/)

# Spectral Reconstruction with GPR

- Gaussian process for spectral function

$$\rho(\omega) \sim \mathcal{GP}(\mu(\omega), C(\omega, \omega'))$$

- Gaussian distribution for correlator via KL integral

$$G_i \sim \mathcal{N} \left( \int d\omega K(p_i, \omega) \mu(\omega), \int d\omega d\omega' K(p_i, \omega) C(\omega, \omega') K(p_j, \omega') \right) \\ \equiv \mathcal{N}(\tilde{\mu}_i, \tilde{C}_{ij})$$

- Inverse inference step

$$\rho(\omega) | G_i \sim \mathcal{GP} \left( \mu(\omega) + \sum_{i,j=1}^{N_G} \int d\omega' K(p_i, \omega') C(\omega', \omega) \left( \tilde{C} + \sigma_n^2 \cdot \mathbf{1} \right)_{ij}^{-1} (G_j - \tilde{\mu}_j) \right)$$

$$C(\omega, \omega') - \sum_{i,j=1}^{N_G} \int d\omega' d\omega'' K(p_i, \omega') C(\omega', \omega) \left( \tilde{C} + \sigma_n^2 \cdot \mathbf{1} \right)_{ij}^{-1} K(p_j, \omega'') C(\omega'', \omega)$$

- Kernel parametrization, e.g. radial basis function

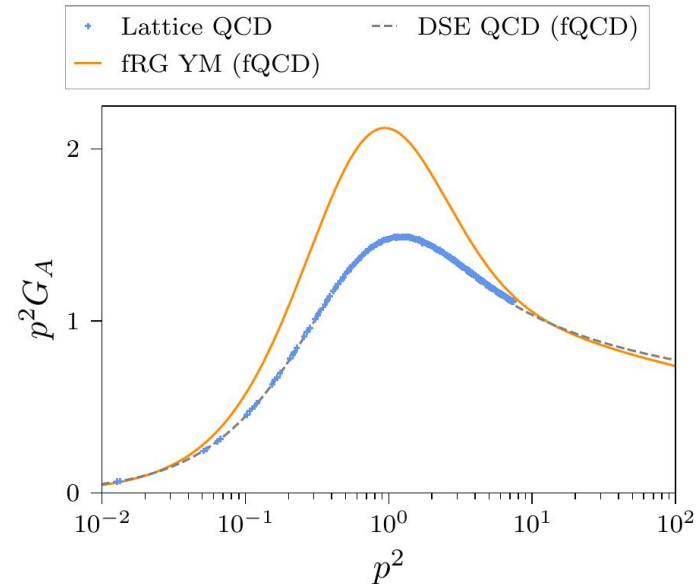
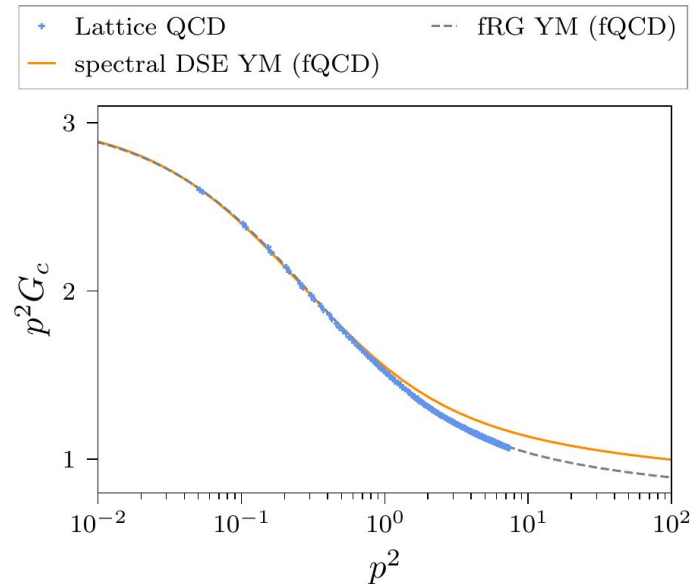
$$C(\omega, \omega') = \sigma_C^2 \exp\left(-\frac{(\omega - \omega')^2}{2l^2}\right)$$

Further details: [doi:10.1093/gji/ggz520](https://doi.org/10.1093/gji/ggz520)

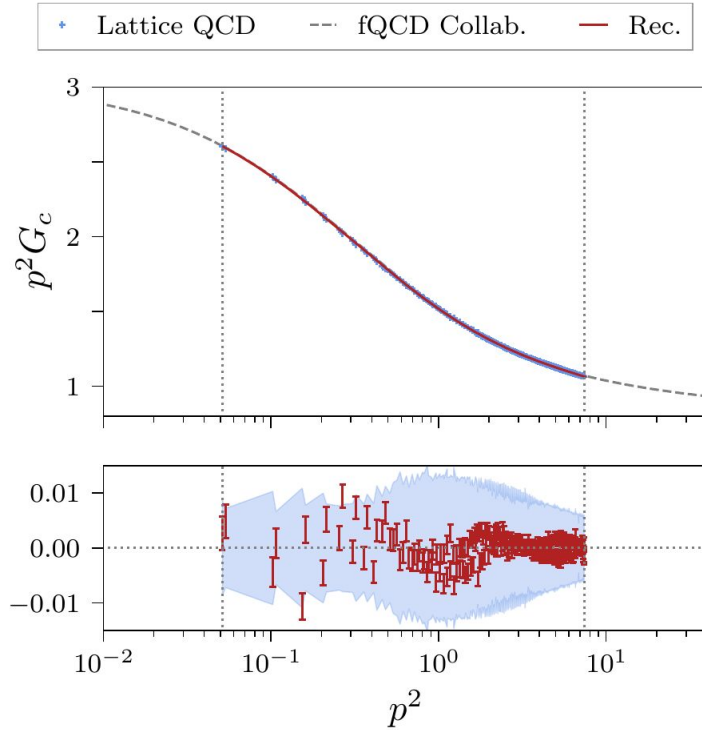


# Input Data & Benchmarks

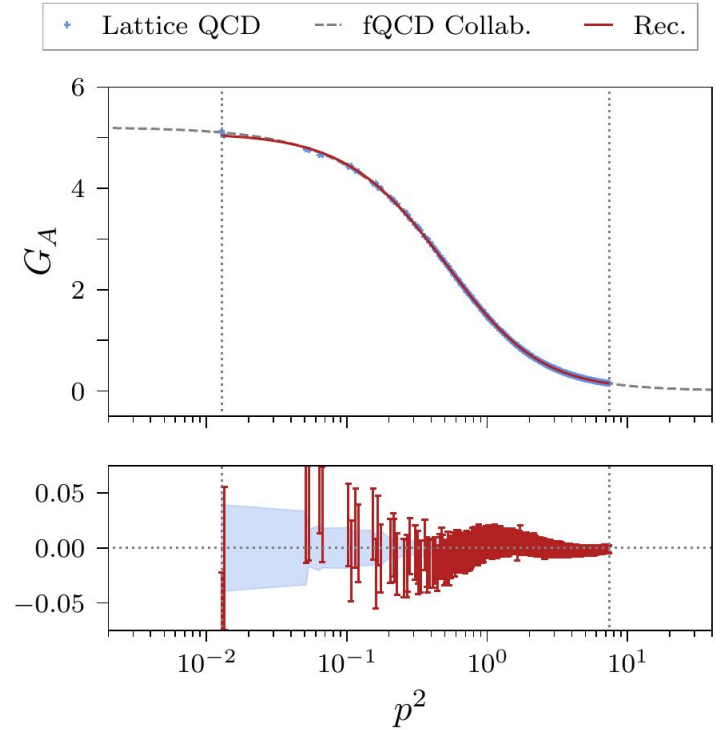
- Lattice: 2+1 flavor, Iwasaki + DWF,  $m_\pi = 139$  MeV, courtesy of RBC/UKQCD collab.  
1902.08148, 1912.08232
- Functional: 2+1 flavor & Yang-Mills, DSE & fRG, courtesy of fQCD collab.  
1605.01856, 1706.06326, 1804.00945, 1909.02991, 2002.07500, 2102.13053, 2103.16175



# Results

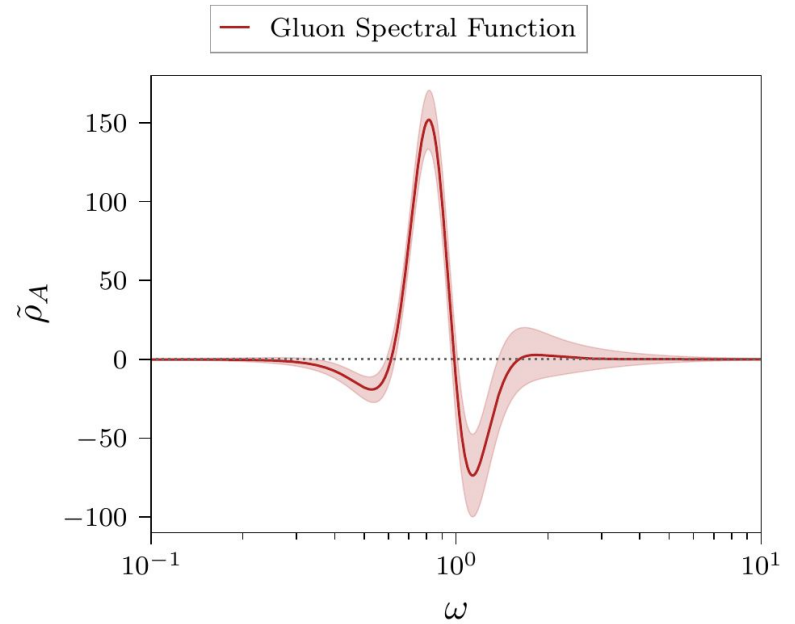
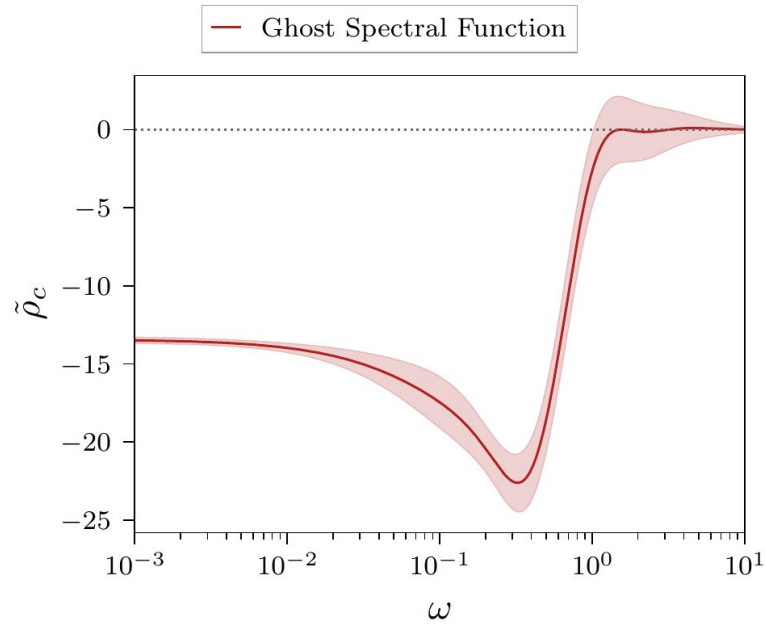


MSE:  $\sim 5e-6$

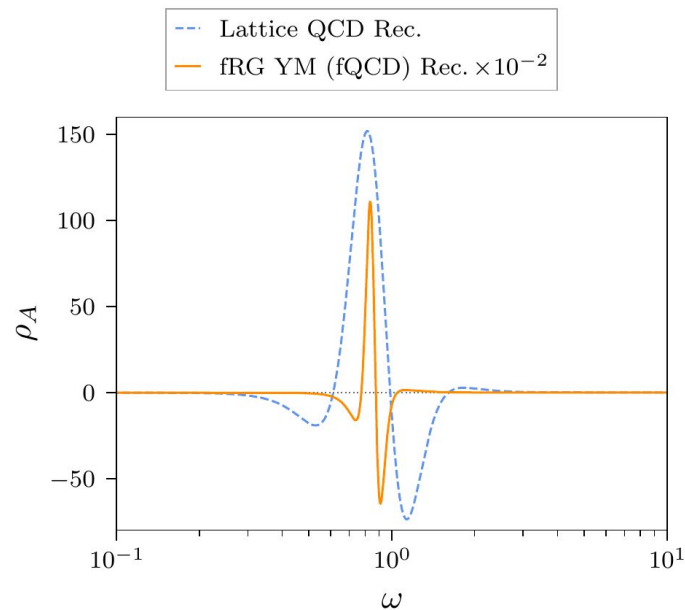
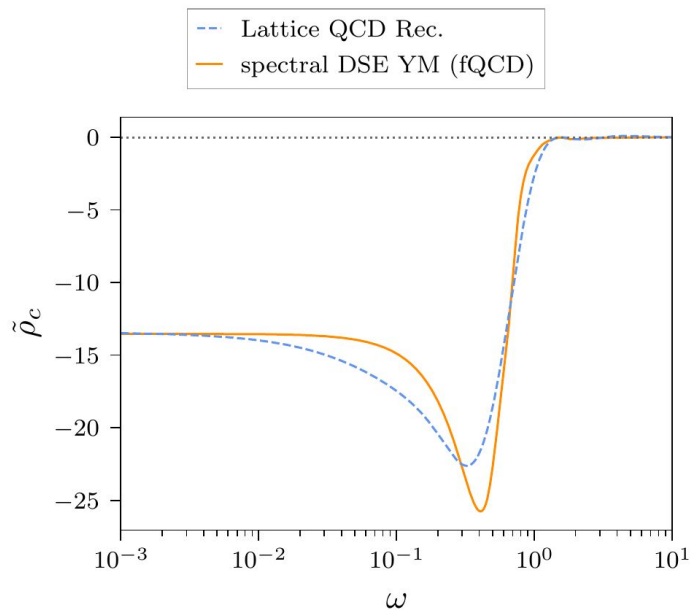


MSE:  $\sim 4e-5$

# Results

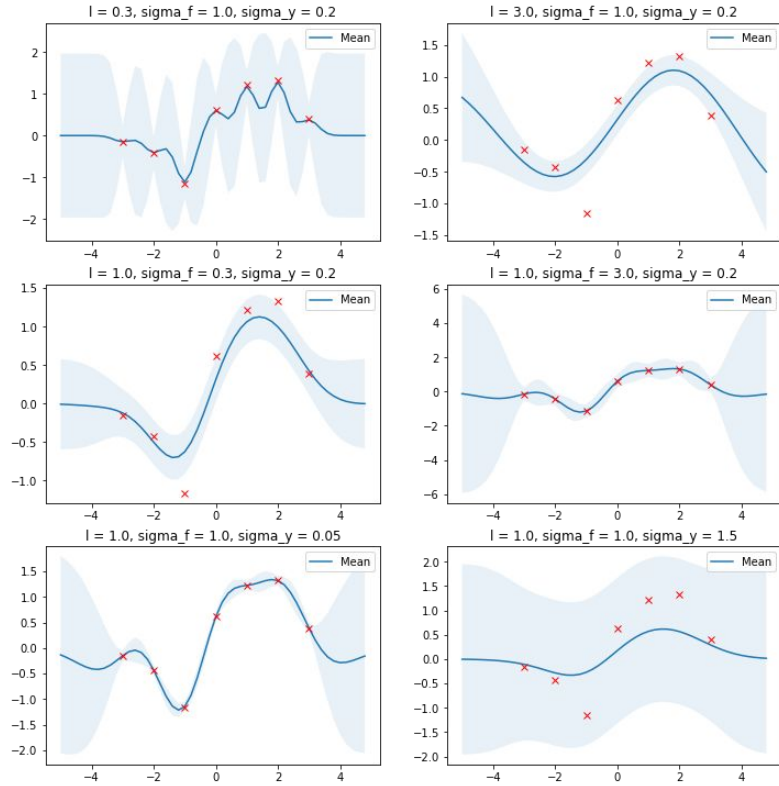


# Comparison to Yang-Mills Results

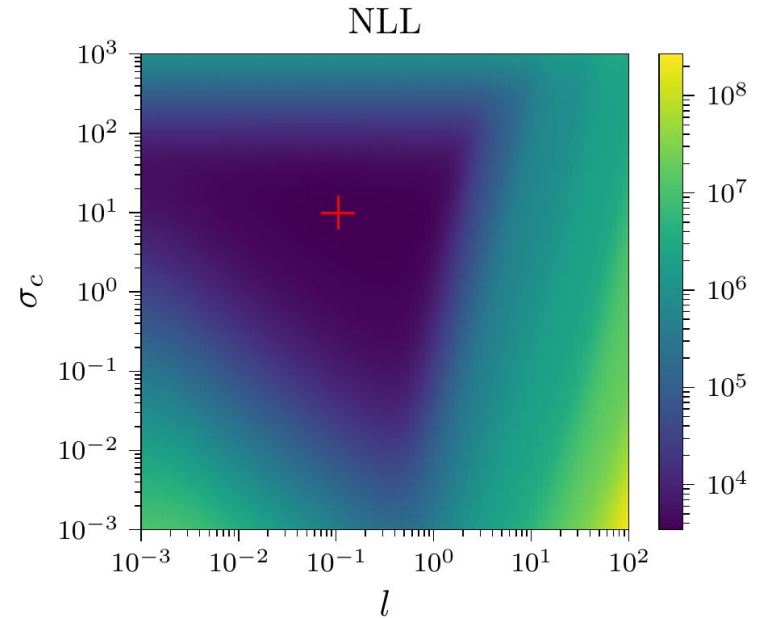


- Leading peak positions of the gluon spectral function:  
QCD:  $\omega \sim 0.818$ , Yang-Mills:  $\omega \sim 0.835$

# Hyperparameter Optimization



$$p(\hat{\rho}|\alpha) = \left( (2\pi)^N \det(\hat{\mathbf{C}}_\alpha + \sigma_n^2 \cdot \mathbf{1}) \right)^{-\frac{1}{2}} \cdot \exp\left( -\frac{1}{2}(\hat{\rho} - \hat{\mu})^T (\hat{\mathbf{C}}_\alpha + \sigma_n^2 \cdot \mathbf{1})^{-1} (\hat{\rho} - \hat{\mu}) \right)$$



# Outlook

- Building blocks of diagrammatic representations for transport coefficients, bound state equations (Bethe-Salpeter, Faddeev)
- First-principle QCD inputs for phenomenological approaches to transport processes
- Improvements to reconstruction approach: custom kernels, hyperkernels, deep kernel learning, hyperpriors, derivatives

Next steps: quark spectral functions & finite temperature



Thank you!

