

# Inverse problem: Gaussian Processes and Backus Gilbert

---

Alessandro Lupo

Ongoing work with L. Del Debbio, M. Panero, N. Tantalò



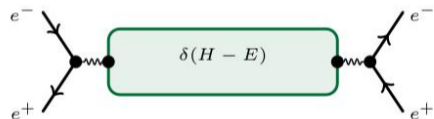
UKLFT Annual Meeting, Cambridge, March 27th 2023

# Inverse problems

- Computing the **spectral densities** associated to a lattice correlators

$$C(t) = \int_0^\infty dE \rho(E) e^{-tE}$$

- Allow access to: inclusive decay rates, scattering amplitudes, finite-volume spectrum . . .
- Ill-posed** in presence of **error on the data**.
- This talk: two approaches, **Backus Gilbert** (BG) and **Gaussian Processes** (GP).



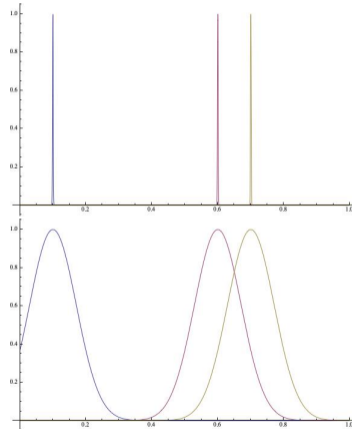
# Generalities

Regardless of the approach

- The spectral density **must be smeared**, so that it is a smooth function even in a finite volume

$$\rho_{\sigma}(\omega) = \int_0^{\infty} dE \Delta_{\sigma}(\omega, E) \rho(E)$$

- Must use a **regularisation**. Ideally results should not depend on anything unphysical (within statistical errors).
- Reliable **estimates of the systematics** are necessary.
- More in Max Hansen's talk tomorrow



# Backus Gilbert

- (Hansen Lupo Tantalo 2019) Solve directly for a **smearred spectral density**  $\rho_\sigma(E)$ . Aim to find  $g_t$  that span the **targer kernel**.

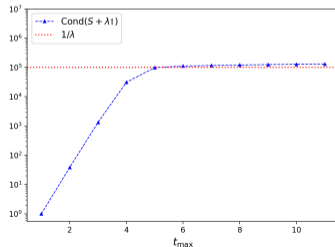
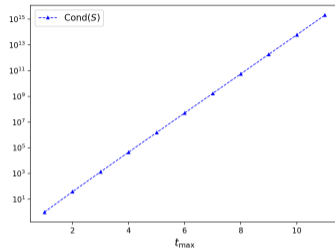
$$\sum_{t=1}^{\infty} g_t e^{-tE} = \Delta_\sigma(\omega, E) \implies \rho_\sigma(E_*) = \sum_{t=1}^{\infty} g_t C(t)$$

- $g_t$  obtained minimising

$$\underbrace{\int_0^\infty dE \left| \sum_{t=1}^{t_{\max}} g_t e^{-tE} - \Delta_\sigma(\omega, E) \right|^2}_{\text{Provides exact solution}} + \lambda \underbrace{\vec{g} \cdot \text{Cov}_d \cdot \vec{g}}_{\text{Regularises}}$$

- Amounts to invert the matrix  $T$ . The first terms express the **ill defined nature** of the problem.

$$T^{BG} = \int_0^\infty dE e^{-(t+r)E} + \lambda \text{Cov}_d$$



# Bayesian Inference with Gaussian Processes

- Aim for a **probability distribution** over a functional space of possible **spectral densities**
- GP: consider the stochastic field  $\mathcal{R}(E)$  **Gaussian-distributed** around the **prior** value  $\rho_{\text{mod}}(E)$  with covariance  $S(E, E')$ .

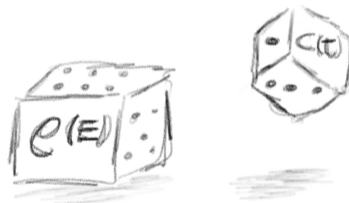
$$\mathcal{GP}(\mathcal{R}(E) - \rho_{\text{mod}}(E), S(E, E'))$$

- Similarly, assume that **observational noise** is Gaussian:  $\eta(t)$

$$\mathcal{G}(\eta, \text{Cov}_d) = \exp\left(-\frac{1}{2} \vec{\eta}^T \text{Cov}_d \vec{\eta}\right)$$

- The relation between the two induces a **correlation**.

$$C_{\text{obs}}(t) = \int dE e^{-tE} \mathcal{R}(E) + \eta(t)$$



# Gaussian Processes vs Backus Gilbert

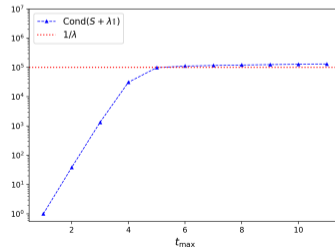
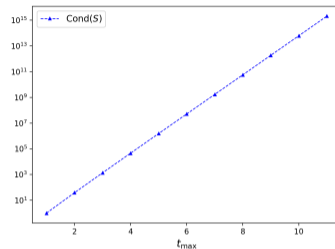
- Given the previous relation, the Bayes theorem yields the **joint distribution** for  $\rho(\omega)$  and  $C_{\text{obs}}$  (Pawlowski et al. 2020, Del Debbio et al. 2021)
- Central value of **posterior** distribution gives a prediction for  $\rho(\omega)$

$$\rho(\omega) = \rho_{\text{mod}}(\omega) + \int dE e^{-tE} S(E, \omega) (T^{\text{GP}})_{\text{tr}}^{-1} (C_{\text{obs}}(r) - C_{\text{mod}}(r))$$

$$T^{\text{GP}} = \int dE_1 dE_2 e^{-tE_1} S(E_1, E_2) e^{-tE_2} + \text{Cov}_d$$

- (1) Compare the matrix inverted with Backus Gilbert. **Numerically** both approaches have the **same regularisation**.

$$T^{\text{BG}} = \int_0^\infty dE e^{-(t+r)E} + \lambda \text{Cov}_d$$

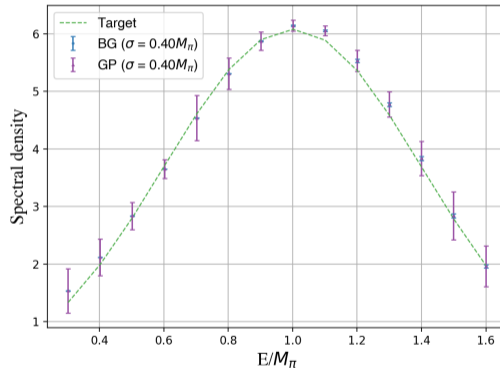


# Correspondence

- BG (Hansen Lupo Tantalò 2019): look for a solution **smear**ed with a **Gaussian**.
- Look for the probability distribution of a spectral density **smear**ed with a **Gaussian**. Requires to generalise the previous equations. (Valentine, Sambridge 2020)
- Set up GP with a **specific prior**: the probability distribution for the smeared spectral density is centered around  $\rho_{\sigma}^{BG}$ :

$$S(E_1, E_2) = \frac{\delta(E_1 - E_2)}{\lambda}, \quad \rho_{\text{mod}} = 0$$

- Only difference: estimate of the **statistical error**.



# Conclusions and outlook

$$S(E_1, E_2) = \frac{\delta(E_1 - E_2)}{\lambda}, \quad \rho_{\text{mod}} = 0$$

- BG and GP both provide an answer in terms of a smeared version of the unknown function.
- By looking for an answer smeared with a **given function** we obtain the **same prediction**
- BG side: ideally changes in algorithmical parameters (e.g.  $\lambda$ ) cannot affect physics  $\implies$  results must fluctuate within statistical error.
- In the **Bayesian language**: ideally the result should not depend on the priors within statistical errors.
- **In progress**: relation between estimates for statistical error, study of systematics, ...

