

Comparison to relativistic free spectrum (see. hep-lat/0509004)

VIII

$$g(\omega) = \Theta(\omega^2 - 4M^2) \frac{N_c}{8\pi\omega} \sqrt{\omega^2 - 4M^2} (1 - 2\eta_F(\omega)) (\omega^2 \kappa + 4M^2 \kappa) + 2\pi\omega \delta(\omega) N_c \propto \frac{\omega^2}{\omega^2}$$

Now the lattice NRQCD version: We get the dispersion relation from our time evolution operator $K_{x,z+1} = (1 - \alpha \frac{P^2}{2m}) K_{x,z} \Rightarrow \alpha E_p = -\log(1 - \frac{P^2}{2m\alpha})$

Exercise: Compute the NRQCD free spectral function for $M_\Lambda = 5$.

Let us have a look at some actual real-world NRQCD data.

Hot QCD, $N_f=2+1$, HISQ ensembles $48^3 \times 17$ ($T>0$) $48^3 \times 32, 48, 64$ ($T=0$)

$M_b a \in [2.8 \dots 0.9]$ $n=4$ [Fig 8] [Fig 9] (see also: 1409.3630; 1402.6210; 1109.4496)

\Rightarrow Notice mass difference between different lattice spacings \rightarrow NRQCD energy shift

\Rightarrow First hint at in-medium modification from correlator ratios. [Fig 10] [Fig 11]

Correlators only give us information about global in-medium changes but we are interested in changes of individual states. Need spectral information (mass & width @ $T>0$). One peak acquire thermal width effective mass analysis fails (no plateau!).

Spectral function reconstruction using Bayesian inference

In general we have the relation $D(c) = \int d\omega K(c, \omega) g(\omega)$

which needs to be inverted. Since g can contain many features

needs to be well resolved along ω . $D_i = \sum_{c=1}^{N_c} \int d\omega_k K(c, \omega_k) g_c$

Inversion is ill-posed and ill-conditioned: Naive inversion in the case $N_c = N_\omega$ leads to exponential increase of noise.
 $N_c \ll N_\omega$ $D_i = D_i^{\text{ideal}} + \eta$ η solutions to $\zeta^2 \propto \eta^2$

Question: How to systematically regularize the problem?

Personal answer: Bayesian inference that allows to incorporate additional prior information on the spectrum. Subjective view of plausibility, assign $P[X]$ even if X is not random variable.

Multiplication law
for prob. ↓

$$P(S, D, I) = P(S|D, I) \cdot P(D|I) > P(D|S, I) P(S|I) >$$

$$\text{Posterior} \\ P[S|D, I] = \frac{\text{↑}}{\text{test function}} \frac{P[D|S, I] P[S|I]}{P[D|I]}$$

$$\text{Likelihood Prior} \\ \frac{P[D|S, I] P[S|I]}{P[D|I]}$$

see also:
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Likelihood: How compatible is the data with current spectrum?

Prior: How compatible is \hat{g} with prior information.

- For sampled data sets, due to the law of large numbers we can assume Gaussian distributed data: $P(D|g, I) = e^{-L} \quad L = \sum_{i,j} (D_i - D_i^e) C_{ij}^{-1} (D_j - D_j^e)$

- The second ingredient is the prior probability

$$P(g|I) = e^{-\alpha S(g, m)}$$

α is a so called hyperparameter that weights influence of data vs. prior information.

Prior information enters in two ways: By the functional form of S and by the choice of a function m , which fulfills $\frac{\delta S}{\delta g}|_{g=m}=0$ the so called default model. By definition it corresponds to the correct spectrum in the absence of data.

\Rightarrow Eventually $\left. \frac{\delta}{\delta g} P(g|D, I) \right|_{g=g_{\text{Bayes}}} = 0$ defines the most probable spectrum in the Bayesian sense. Comparison to LS.

On the market different implementations that differ in $P(g|I)$ and handling of α .

- Tikhonov: $S = \int d\omega (g - m)^2$

ture α such that $L = N_T$

(correct spectrum sampled with Gaussian noise gives $L = N_T$)

issue: pulls the result very sharply towards m

towards m

- Bayesian entropy: $S = \int d\omega (g - m - g \log \frac{g}{m})$

ture α such that $P(D|I)$ extremal
(positive definite spectra, Shannon-Jaynes entropy derived from arguments in 2d image reconstruction)

issue: flat directions make numerical search difficult.

- Bayesian regularizer: $S_{\text{BR}} = \int d\omega \left(1 - \frac{g}{m} + \log \left(\frac{g}{m} \right) \right)$

assure no knowledge of α and integrate out using $P(g|I)$
entire $L = N_T$ in addition.

Issue: for small # of datapoints susceptible to ringing artefacts

How to derive the BR regularizer: 4 Axioms (see: 1307.6106)

① Subset independence

Consistently combine prior information in different frequency regimes. (Probabilities multiply)

$$\propto \int d\omega S(g(\omega), m(\omega))$$

② Scale invariance:

(X)

Contrary to statements in the literature, \hat{g} itself does NOT need to behave like a probability distribution. Scaling depends on the corresponding covariogram.

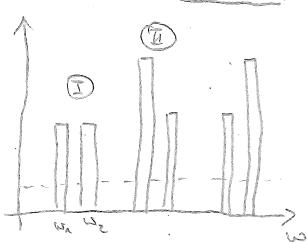
$$S_{\text{QQ}}^{\text{(NDD)}} \sim \sqrt{\omega} \quad S_{\text{QQ}}^{\text{rel}} \sim \omega^2 \quad S_{\text{wL}} \sim \frac{1}{\omega} \quad S_{\text{ENT}} \sim \omega^4$$

To make the results independent of the units used we only allow ratios of quantities to enter with some scaling. $\Rightarrow S \propto \tilde{\chi} \int dw S \left[\frac{g}{m} \right]$

Introduce a positive lag parameter with units $[c_2] = \frac{1}{\text{Hz} \cdot \text{deg}}$.

③ Smoothness:

Where the data does not encode peaked structures the spectrum shall remain smooth. Use here maximally uninformative default model $m(\omega) = m$.



Penalize deviations between neighbouring \hat{g} values: $V_1 = \frac{S_1}{\omega_1}, V_2 = \frac{S_2}{\omega_2}$

$$\text{I vs. II: } 2S(\omega) - S(\omega + \epsilon) - S(\omega - \epsilon) = \epsilon^2 C_2$$

↑ since $\epsilon > 0$
multiplicative factor

↑ same penalty for
I and III

$$\Rightarrow -r^2 S''(\omega) = C_2$$

$$\text{Solution: } S = \tilde{\chi} \int dw \left(C_0 - C_1 \frac{g}{m} + C_2 \log \left(\frac{g}{m} \right) \right)$$

④ Bayesian meaning of S :

$S'(r=1) = 0, S''(r=1) < 0$ (convention $S(r=1) = 0$)
after absorbing overall positive factor into $\tilde{\chi}$

$S_{\text{BR}} = \alpha \int dw \left(1 - \frac{g}{m} + \log \frac{g}{m} \right)$ is strictly concave $\frac{\partial^2 S}{\partial g^2} < 0$,
i.e. $-L + \alpha S$ has unique extremum.

How to handle α : Make its role explicit and marginalize

$$\begin{aligned} P(S, D, \alpha, m) &= P(D | S, \alpha, m) P(S | \alpha, m) P(\alpha | m) P(m) \\ &= P(\alpha | S, D, m) P(S | D, m) P(D | m) P(m) \end{aligned}$$

$$\begin{aligned} P(D | S, \alpha, m) &= P(D | S, m) \\ P(\alpha | m) &= P(\alpha) = 1 \end{aligned}$$

$$\Rightarrow P(S | D, m) = \frac{P(D | S, m)}{\int dk P(S | \alpha, m)}$$

In addition we also enforce $L = N_T$ as further constraint.

Show example of spectral reconstruction with test [Fig 12] [Fig 13]

Different Non-Bayesian methods available

① Backus-Gilbert: Basic idea: if the kernel is a δ -function the correlator equals the spectrum

\Rightarrow Find linear combination of data-points that maximizes "peakedness" of the kernel.

Issue: Implicit prior information in the optimization criterion.

② Padé-approximation: Basic idea: Project the data onto a set of rational basis functions on which the inversion is computed analytically.

Issue: Data needs to be extremely precise, otherwise large oscillations when inverting analytically do not cancel.

Show results from several NRQCD studies (Fig 14) (Fig 15)

Conservative: Temperature changes from different # of data points, need to disentangle method systematics from in-medium physics.

in NRQCD: Since kernel T independent, truncate $T=0$ data set to $N_c^{T>0}$ and re-do reconstruction (as if same spectrum is encoded at higher T)

relativistic: T -dependent kernel, need to compute "reconstructed correlator"

$$G^{\text{rec}}(c, T, T') = \sum_{\substack{c' = c, \Delta c = N_c \\ N_c - N_c + c}}^{N_c} G(c', T) \quad (\text{see also: 1204.4945})$$

Error analysis:

statistical: Jackknife resampling; repeat the reconstruction with a subset of simulated correlators.

Systematic: Change the default model and observe which parts of the reconstructed spectrum remain robust.

BOTH NEED TO BE CARRIED OUT!