

From quarkonium spectral functions to PDFs: tackling inverse problems on the lattice

Alexander Rothkopf

Faculty of Science and Technology
Department of Mathematics and Physics
University of Stavanger

References:

S.Kim, P. Petreczky, A.R., JHEP 1811 (2018) 088

J. Karpie, K. Orginos, A.R., S. Zafeiropoulos arXiv:1901.05408 (accepted at JHEP)

A.R. arXiv:1903.02293

- The real-time challenge

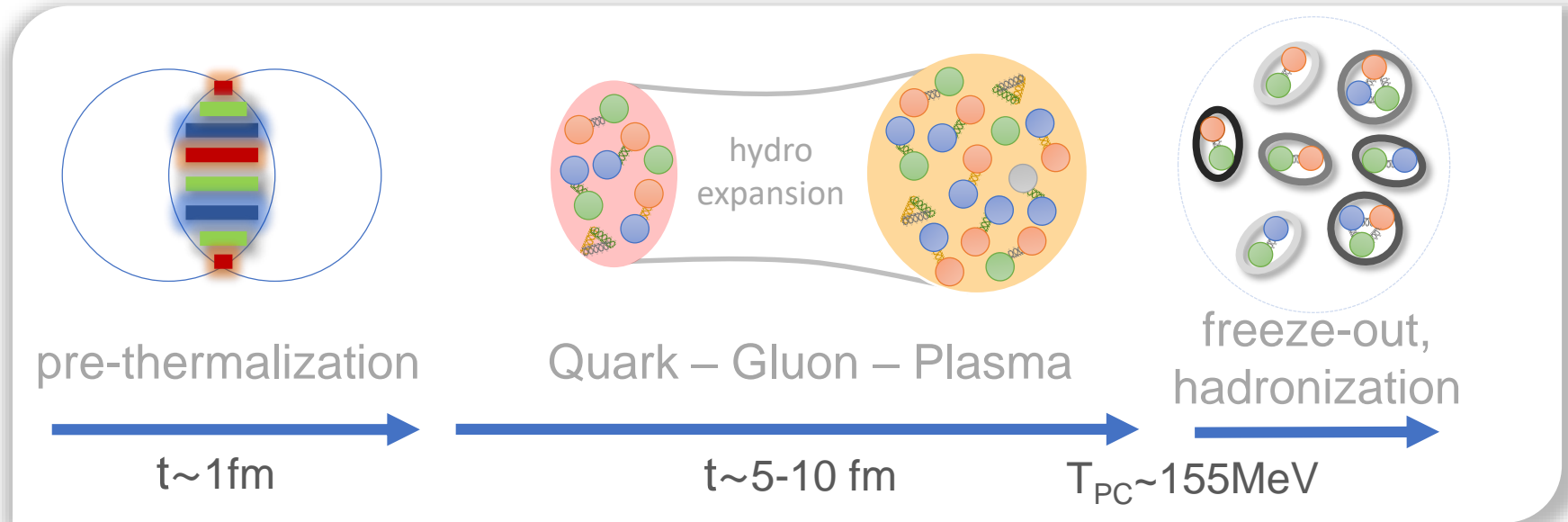
- $T > 0$ quarkonium in-medium spectral functions on the lattice

- Towards parton distribution functions on the lattice

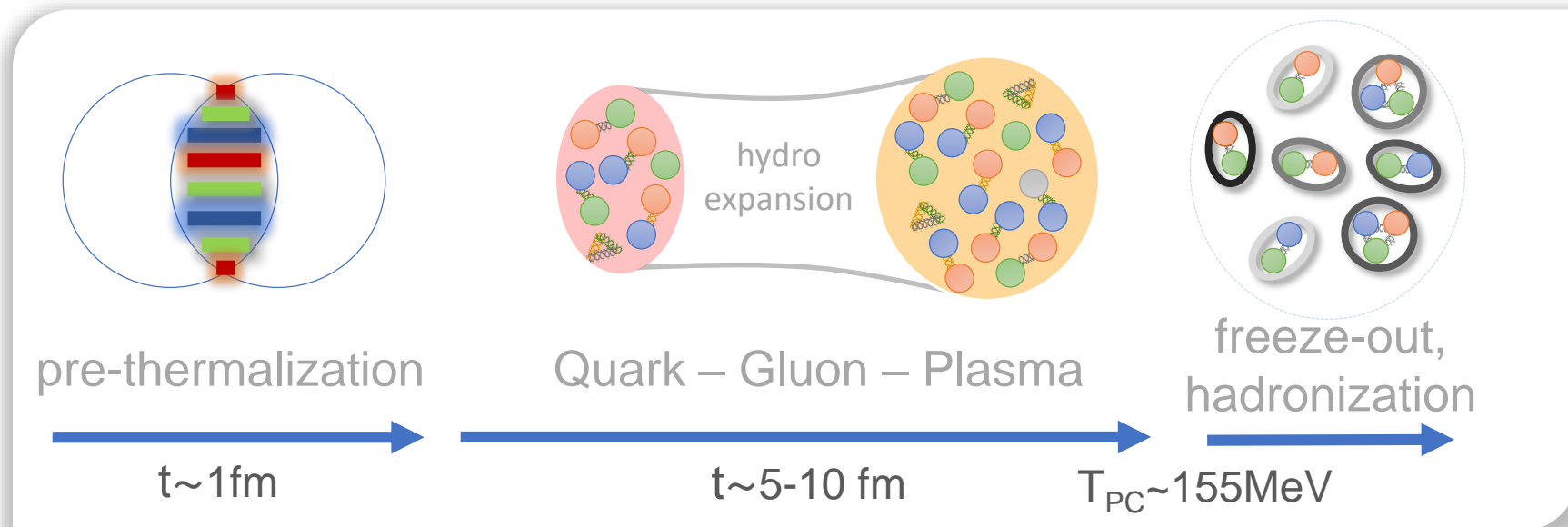
- Conclusion

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The rich non-perturbative physics of HIC

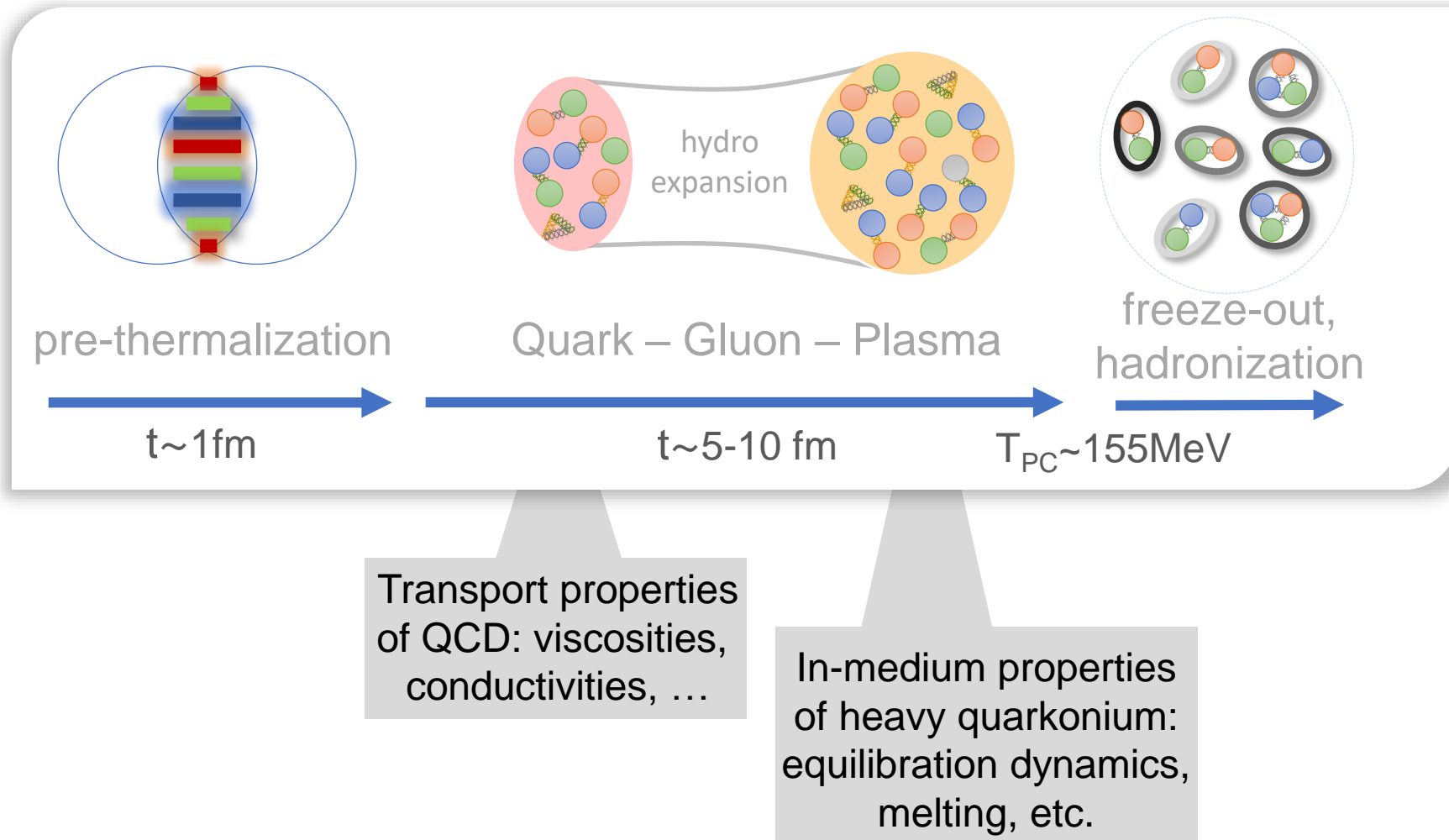


The rich non-perturbative physics of HIC

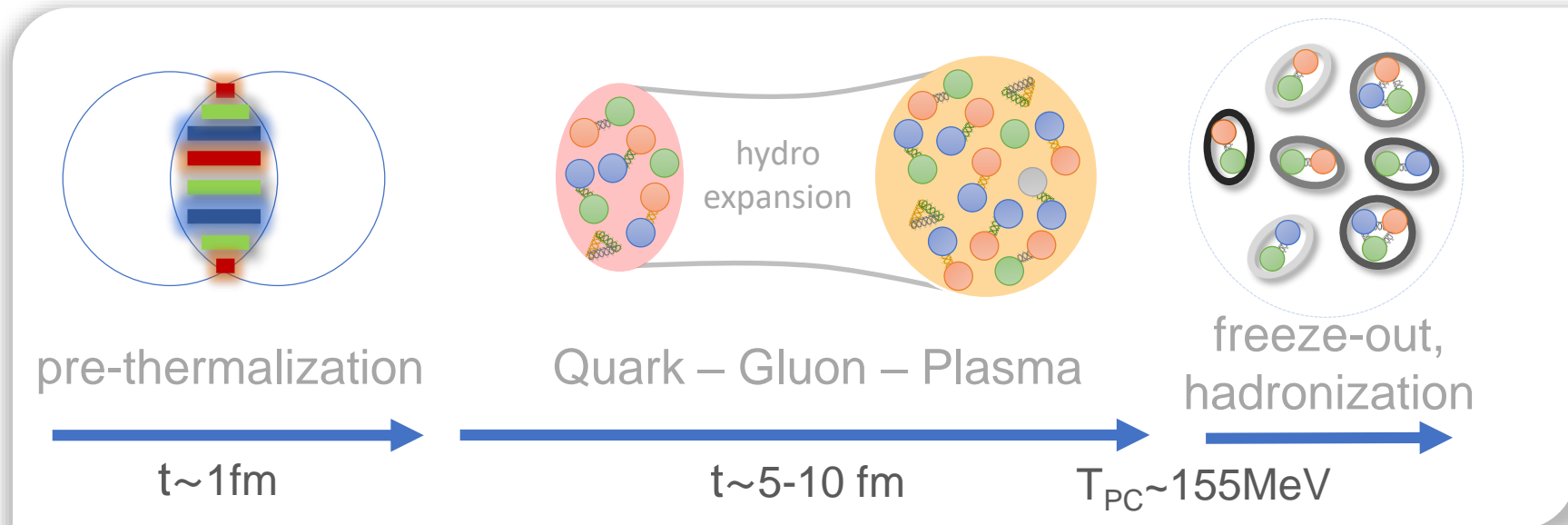


Transport properties
of QCD: viscosities,
conductivities, ...

The rich non-perturbative physics of HIC



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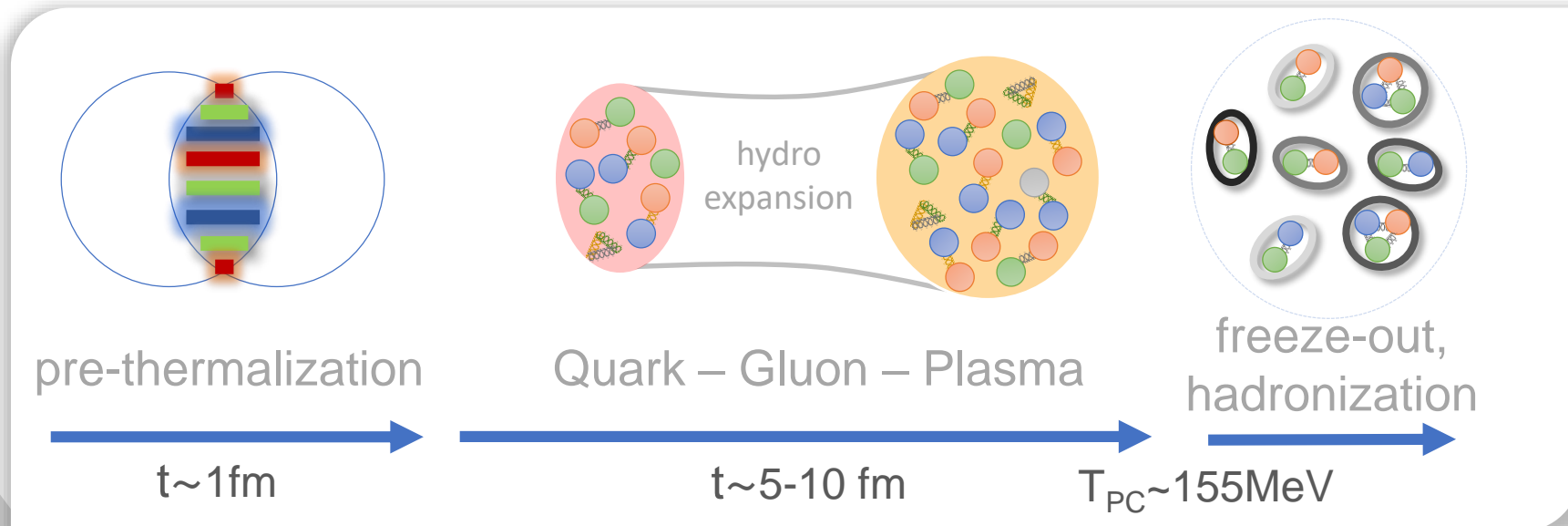


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Hadronization:
change of d.o.f.
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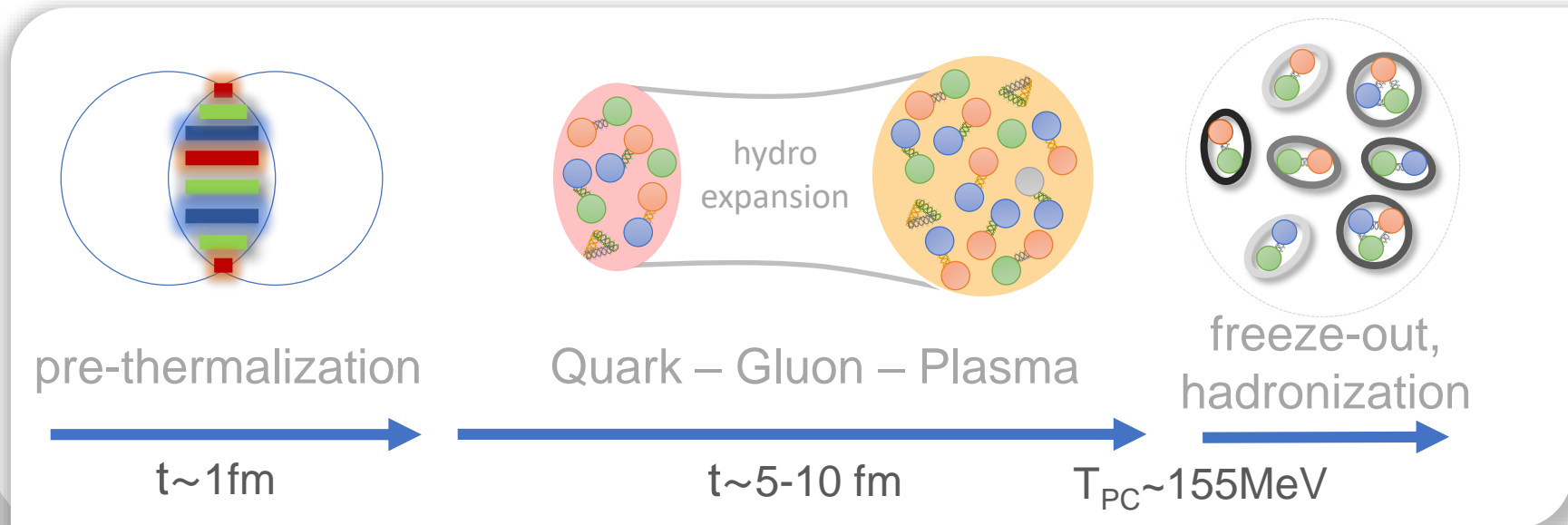
Parton distribution functions of nucleons (and nuclei)

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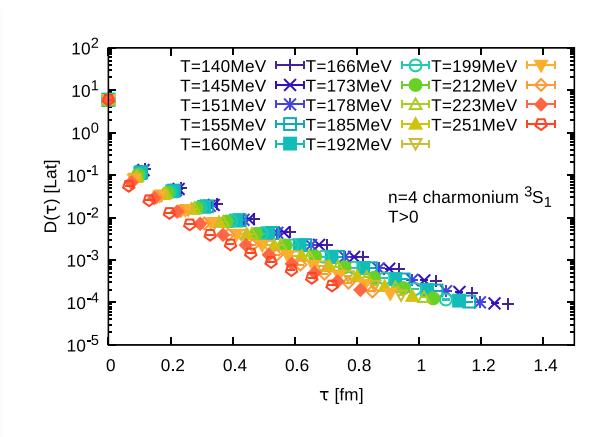
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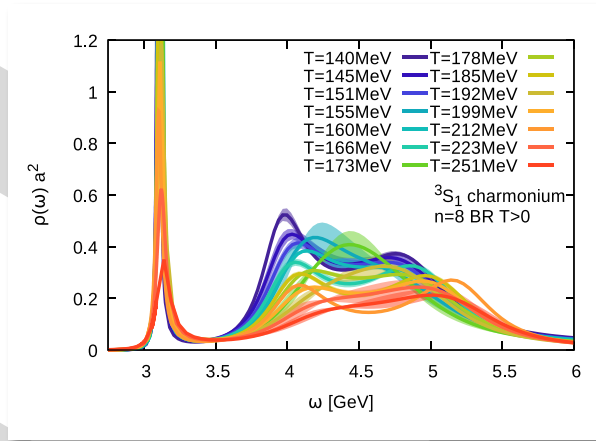
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How can lattice QCD shed light on these dynamical processes?

A common challenge

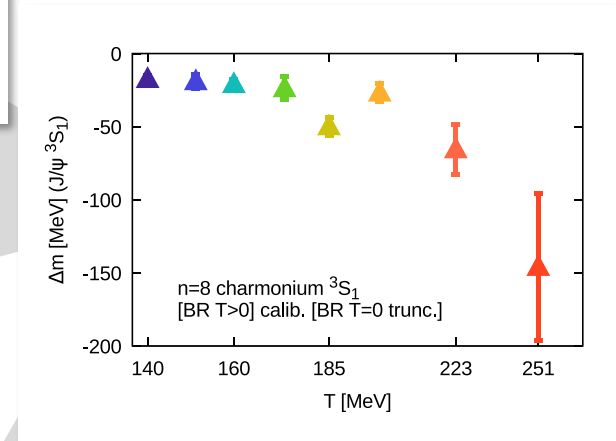


LQCD correlation function in Euclidean time: **D**



real-time quantity in momenta: **r**

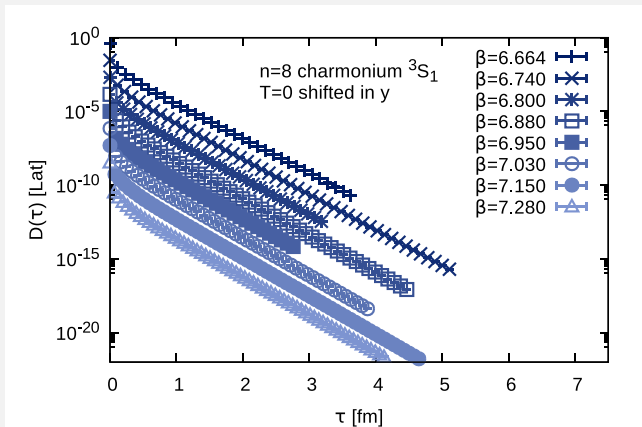
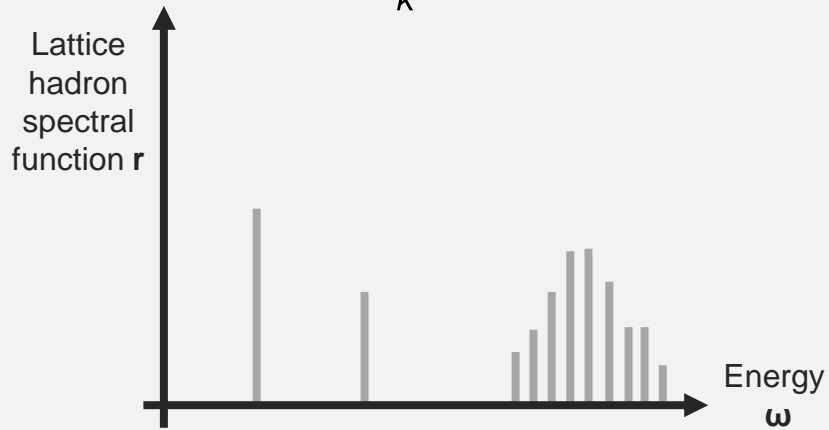
An ill-posed inverse problem



extracted piece of dynamical information

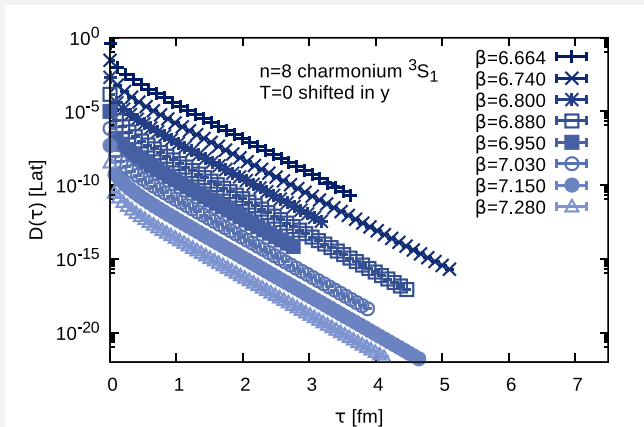
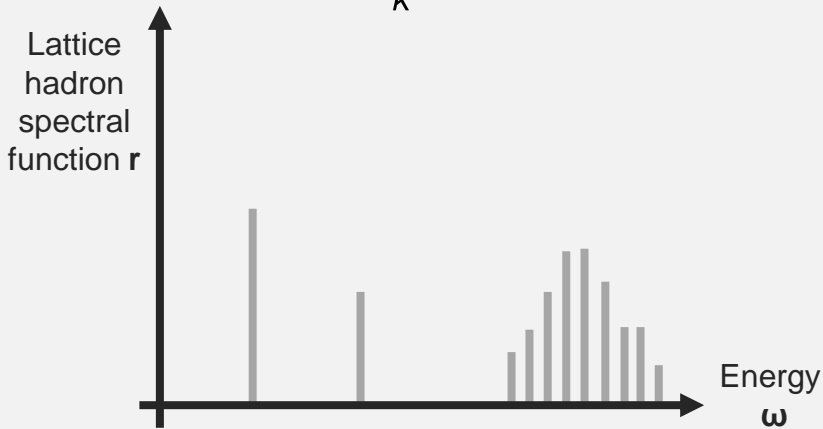
Beyond exponential fitting

$$\langle MM^\dagger \rangle_{T=0} = \sum_k e^{-E_k \tau} |\langle 0 | M | k \rangle|^2$$

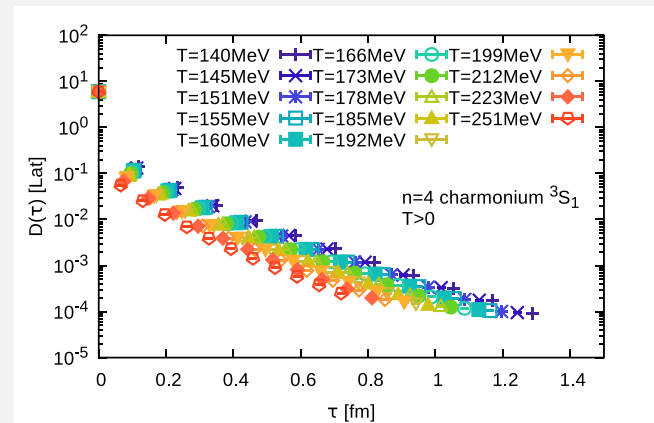
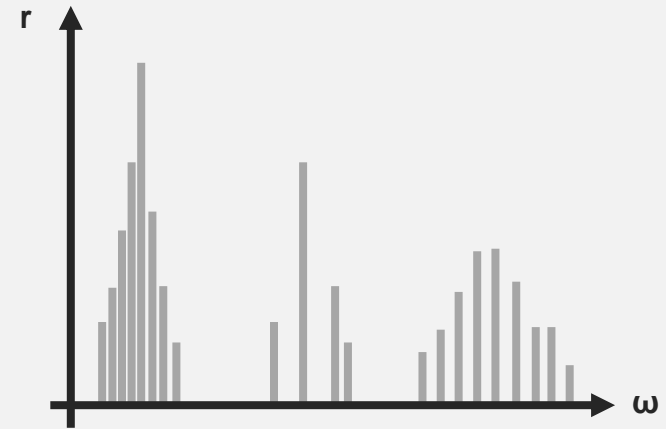


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$$\langle MM^\dagger \rangle_{T>0} = \sum_{kl} e^{-\beta E_k} e^{-(E_k - E_l)\tau} |\langle k | M | l \rangle|^2$$



■ Intricate structure prevents naive use of $T=0$ strategies (e.g. GEVP)

The two main challenges

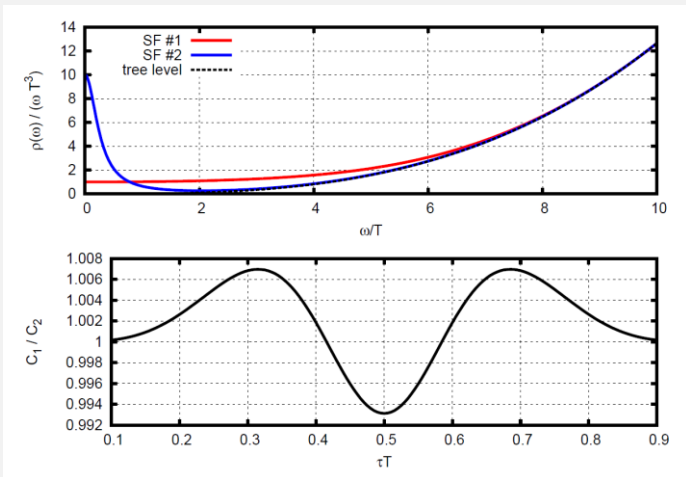
- Invert the spectral representation of the correlator \mathbf{D} : $\mathbf{D} = \hat{K} \mathbf{r}$

$$K_{\omega\tau}^{T=0} = e^{-\omega\tau} \quad K_{\omega\tau}^{T>0} = \frac{\cosh(\omega(\tau - \beta/2))}{\sinh(\omega\beta/2)} \quad K_{x\nu}^{PDF} = \cos(x\nu)$$

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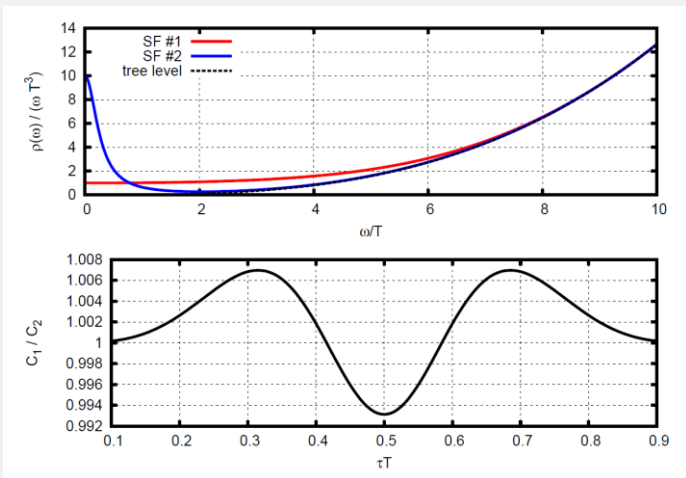


- Exponential **information loss** due to functional form of the kernel

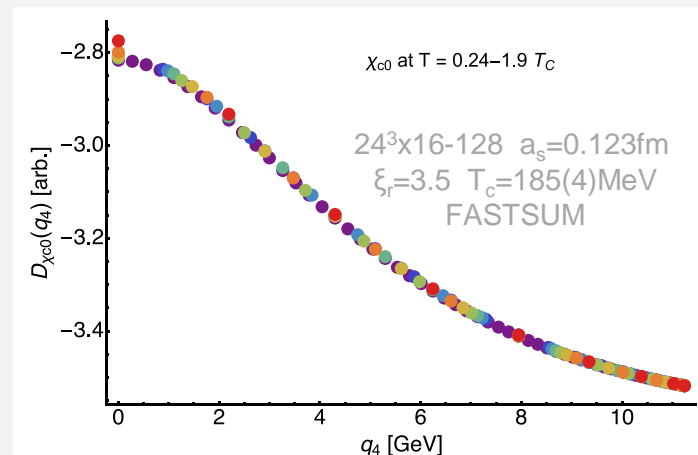
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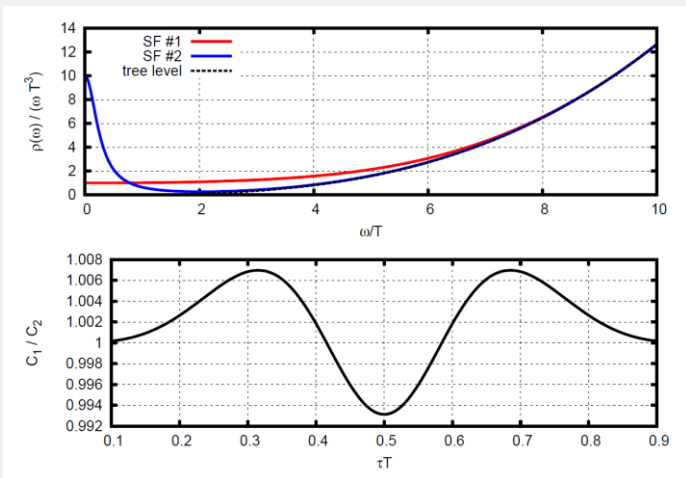


- **Limited Euclidean range** in $T > 0$ QFT leads to coarse Matsubara frequencies
- Cont. limit: resolve only large w_n behavior

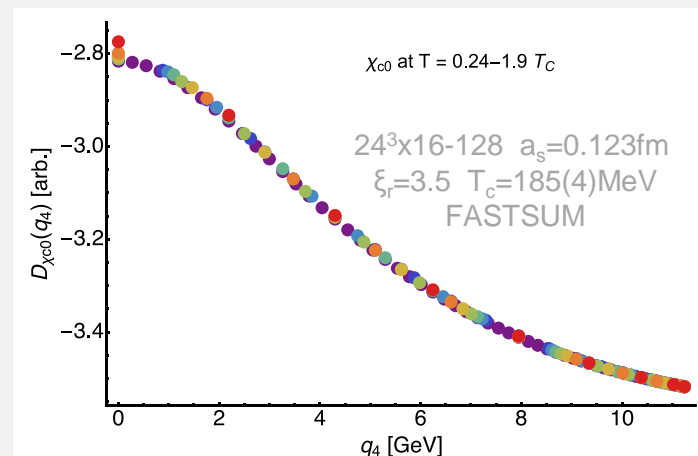
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- How to extract most accurately the information inside lattice data?

The Bayesian strategy

- Extraction of real-time quantities: inversion of ill-conditioned linear transformation

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M. Jarrell, J. Gubernatis, Physics Reports 269 (3) (1996)

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- Prior information in both choice of **prior functional S** and **default model m**

Implementing the Bayesian strategy University of Stavanger

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Enforces positivity.
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Artificially restricts solution space to N_t dimensions around default model. Works well for accurate m .

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Y.Burnier, A.R. PRL 111 (2013) 18, 182003

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- MEM and BR incorporate positivity but no further info on e.g. analytic structure

Both methods are susceptible to favor unphysical oscillatory solutions: **Need to develop better priors**

A few words on Backus-Gilbert

- Simplify the problem as far as possible by linear combinations of input data:

$$\begin{aligned}\tilde{D}(\tau') &= \int d\tau \Sigma(\tau', \tau) D(\tau) \\ &= \int d\omega \int d\tau \Sigma(\tau', \tau) K(\omega, \tau) \rho(\omega)\end{aligned}$$

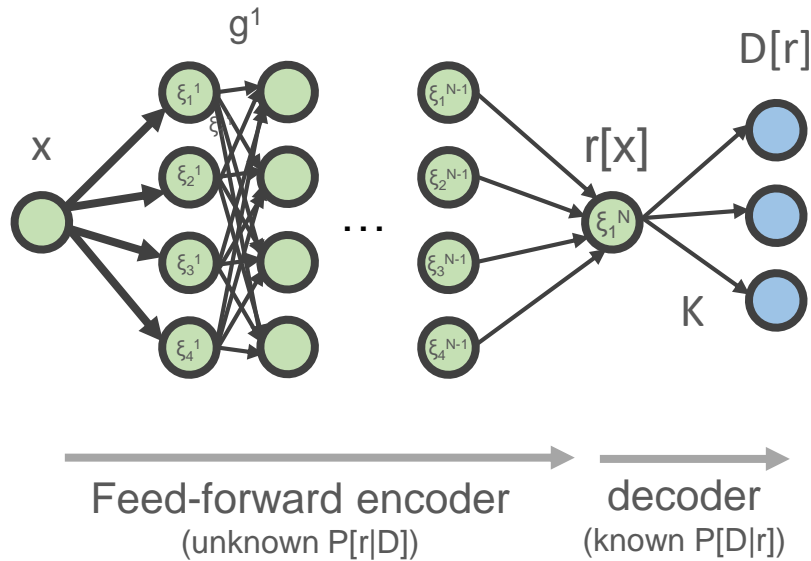
- Task is to construct a resolution function that is as peaked as possible: remains a linear problem

$$\int d\tau \Sigma(\tau', \tau) K(\omega, \tau) \approx \delta(\tau' - \omega)$$

- No default model dependence, but also requires a choice of regularization at intermediate steps

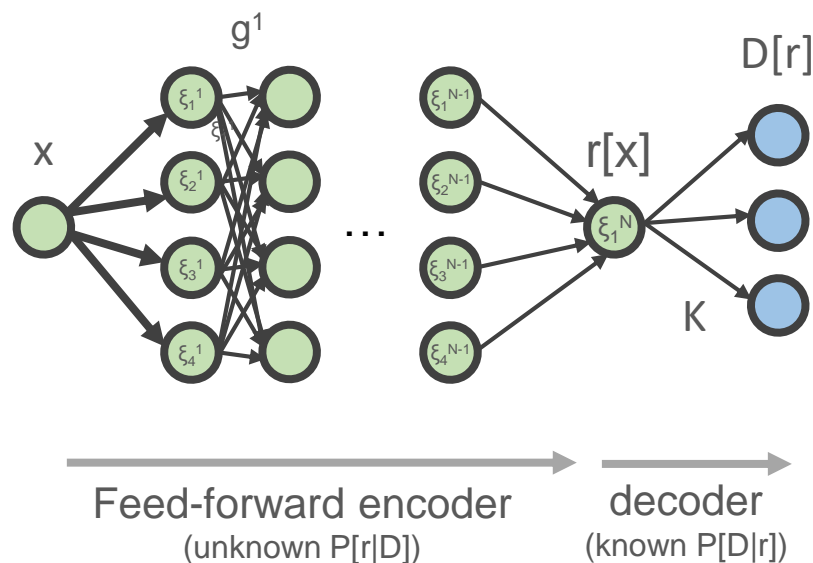
First steps with machine learning

- NN used here as a flexible way to parametrize a function $r(x)$:



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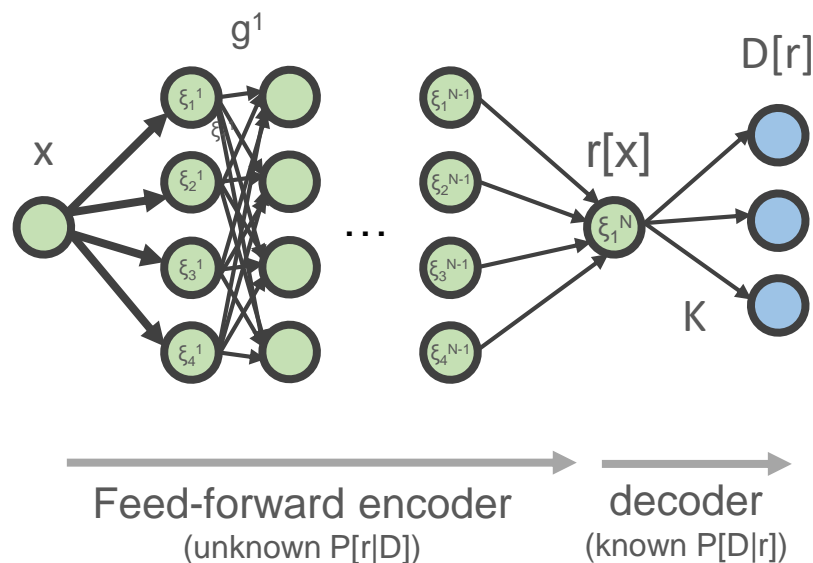
$$\xi_i^{(l)} = g_i^{(l)} \left(\sum_j^{N_{l-1}} w_{ij}^{(l)} \xi_j^{(l-1)} - \theta_i^{(l)} \right)$$

$g(y)$: a non-linear “activation function”,
last layer linear with zero threshold (ReLU)

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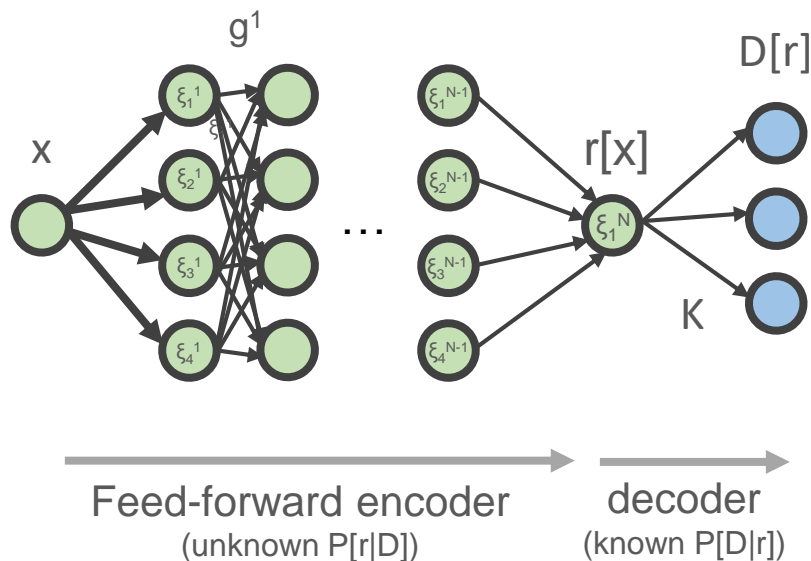
$$T[\xi, D] = \frac{1}{2} \sum_j \left(D_j - \sum_l K_{jl} \xi_l^{(N)} \right)^2$$

Training function is the distance to input data

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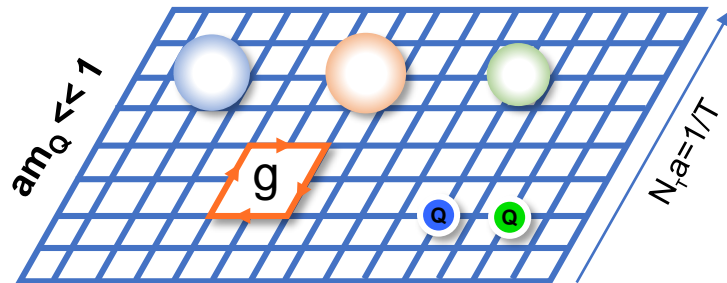
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- Sampling the χ^2 functional space with a particular set of positive definite functions

- The real-time challenge
- **T>0 quarkonium in-medium spectral functions on the lattice**
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Heavy quarks on the lattice

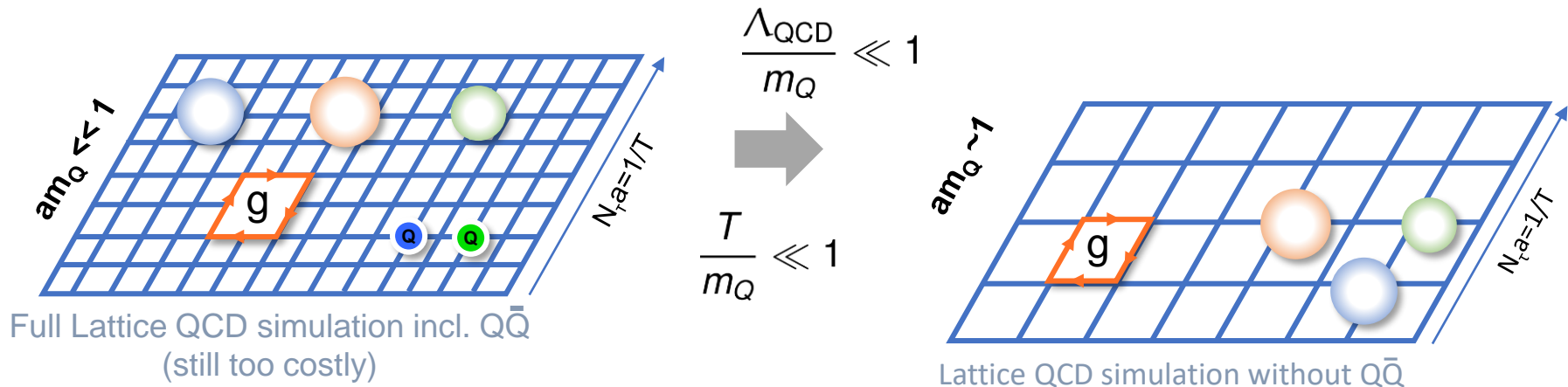
- Exploit separation of scales to treat heavy quarks non-relativistically



Full Lattice QCD simulation incl. $Q\bar{Q}$
(still too costly)

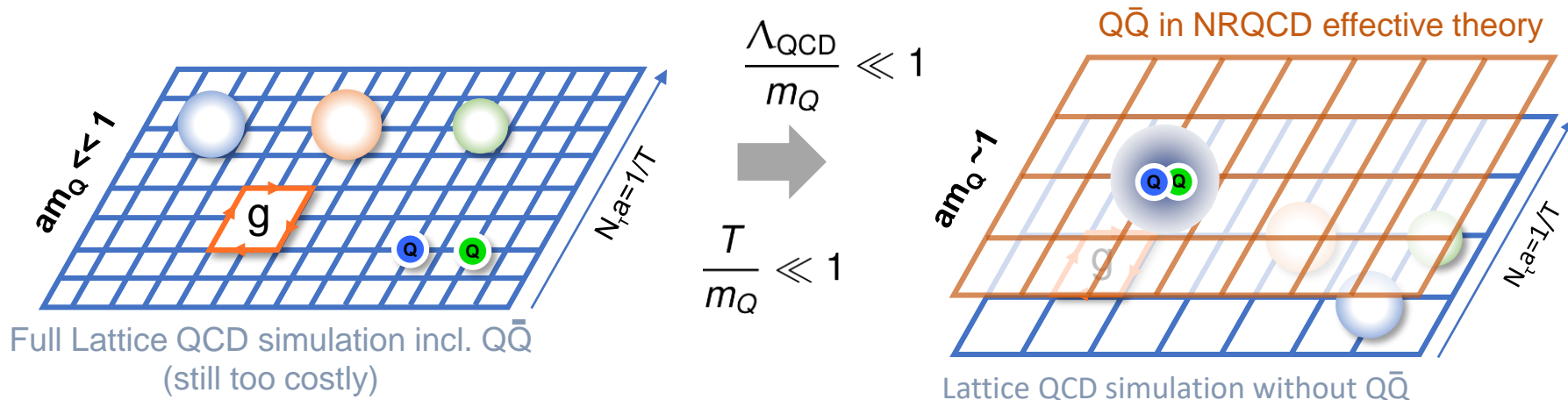
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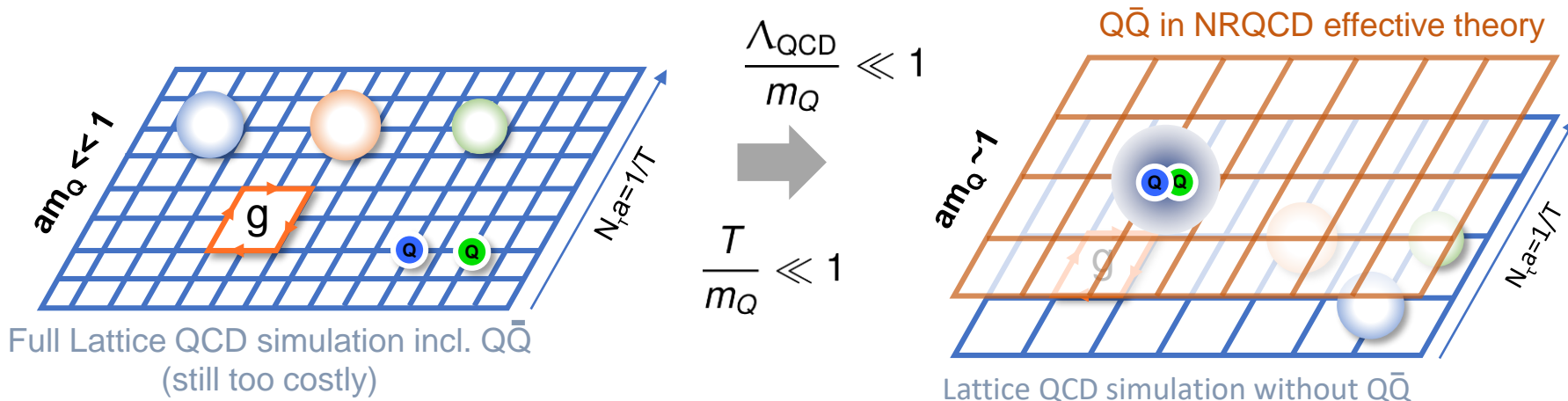


- Lattice Non-Relativistic QCD (NRQCD)** well established at $T=0$, applicable at $T>0$

- no modeling, systematic expansion of QCD action in $1/m_Q a$, includes $v \neq 0$ contributions
Thacker, Lepage Phys.Rev. D43 (1991) 196-208
- our implementation uses $O(v^4)$, i.e. $O(1/(m_Q a)^3)$ and leading order Wilson coefficients

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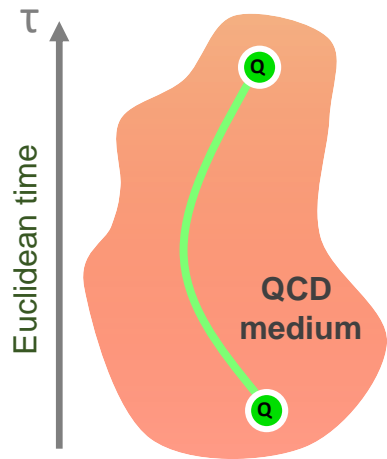
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- Realistic & high statistics** simulations of the QCD medium by HotQCD

HotQCD PRD85 (2012) 054503, PRD90 (2014) 094503

- | | | | |
|---------------------------|-------------------------------|---------------------------|------------------|
| $m_\pi = 161 \text{ MeV}$ | $T = [140 - 407] \text{ MeV}$ | $m_b a = [2.759 - 1.559]$ | Lepage $n_b = 4$ |
| $T=0$ $N_\tau = 32-64$ | $T = [140 - 251] \text{ MeV}$ | $m_c a = [0.757 - 0.427]$ | Lepage $n_c = 8$ |
| $T>0$ $N_\tau = 12$ | | | |
- Use adaptive time discretization for NRQCD stability via Lepage parameter

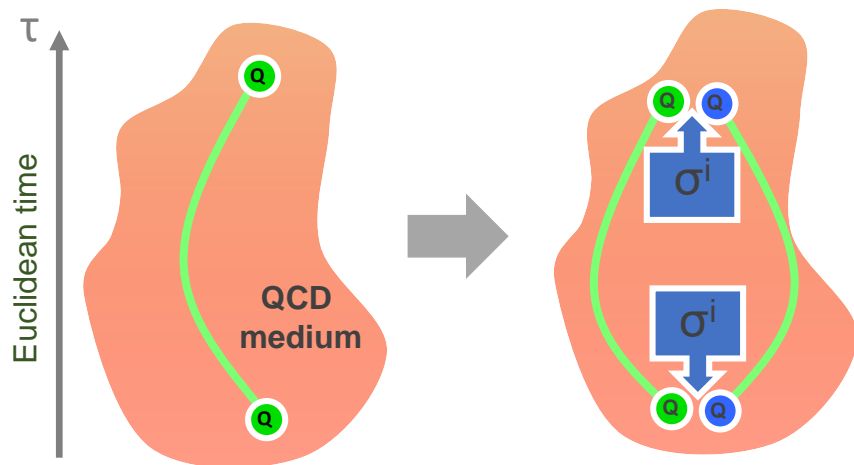
NRQCD Euclidean correlators



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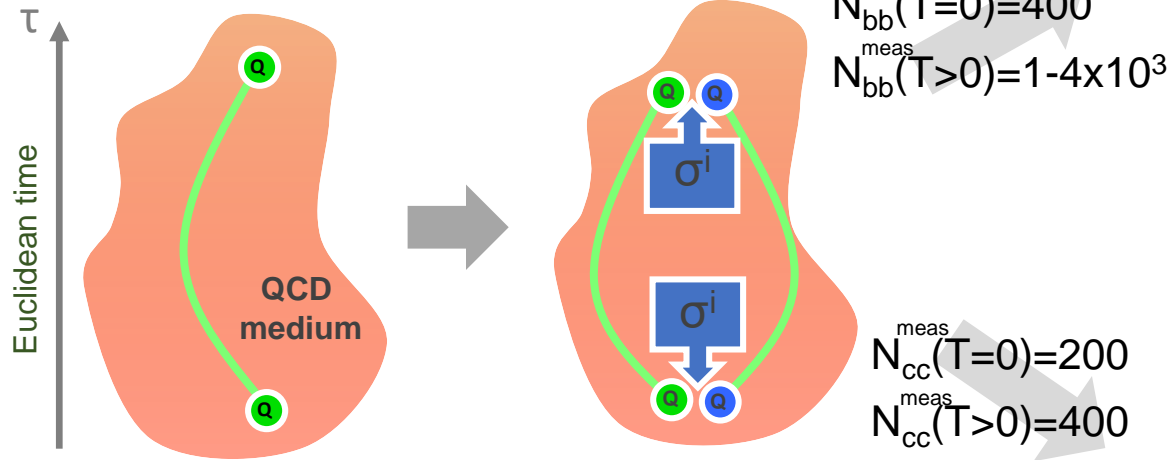
QQ propagator
projected to a certain channel

„correlator of QQ wavefct.

$$D_{J/\psi}(\tau) \triangleq \langle \psi_{J/\psi}(\tau) \psi_{J/\psi}^\dagger(0) \rangle$$

Brambilla et. al. Rev.Mod.Phys. 77 (2005) 1423

NRQCD Euclidean correlators



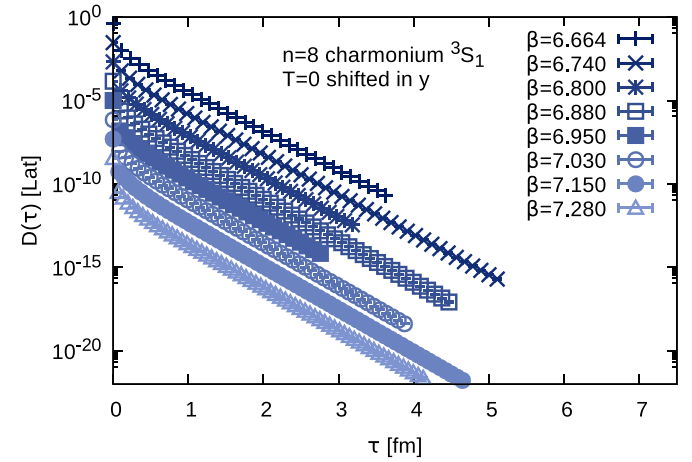
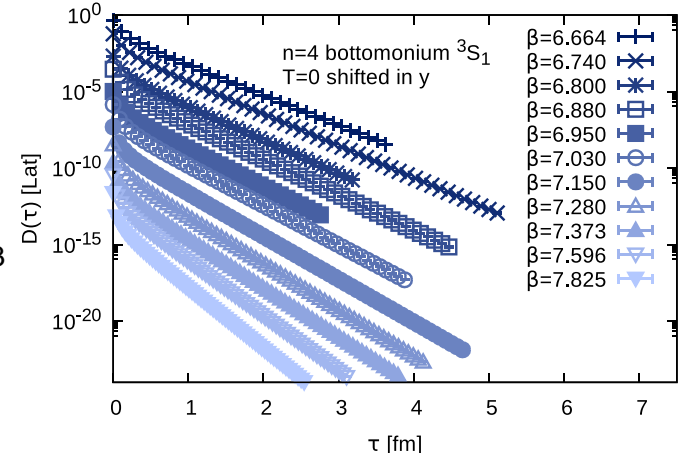
Non-rel. propagator of a single heavy quark G

Davies, Thacker Phys.Rev. D45 (1992)

QQ propagator projected to a certain channel

„correlator of QQ wavefct.
 $D_{J/\psi}(\tau) \triangleq \langle \psi_{J/\psi}(\tau) \psi_{J/\psi}^\dagger(0) \rangle$ “

Brambilla et. al. Rev.Mod.Phys. 77 (2005) 1423



Bayesian spectral reconstruction

- In NRQCD: data D and spectral function ρ are related via **Laplace transform**

$$D(\tau) = \int_{-2m_Q}^{\infty} d\omega e^{-\tau\omega} \rho(\omega) \quad \longleftrightarrow \text{Fourier} \quad D(\mu) = \int_{-2m_Q}^{\infty} d\omega \frac{2\omega}{\omega^2 + \mu^2} \rho(\omega)$$

- Improvement:** incorporate both Euclidean and imaginary frequency data in unfolding

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- Improvement:** incorporate both Euclidean and imaginary frequency data in unfolding
- Introduce modified BR method to better estimate systematic uncertainty

Standard BR method (BR)

$$S_{\text{BR}} = \alpha \int d\omega \left(1 - \frac{\rho}{m} + \log \left[\frac{\rho}{m} \right] \right)$$

- Resolves narrow peaked structures with high accuracy
- Ringing in broad structures if reconstructed from small # of datapoints

„high gain – high noise“

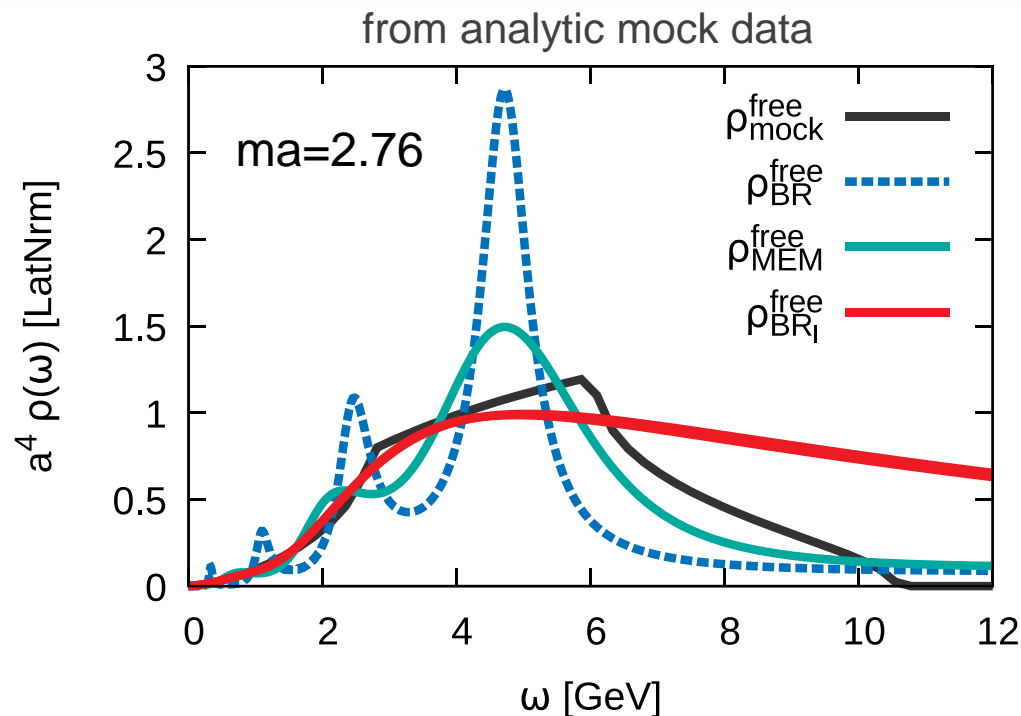
Low ringing BR method (BR_l)

$$S_{\text{BR}_l} = \alpha \int d\omega \left(\kappa \left(\frac{\partial \rho}{\partial \omega} \right)^2 + 1 - \frac{\rho}{m} + \log \left[\frac{\rho}{m} \right] \right)$$

- Introduces penalty on arc length of reconstruction $(dL/d\omega)^2 = 1 + (d\rho/d\omega)^2$
- Efficiently removes ringing but may lead to overestimated peak widths

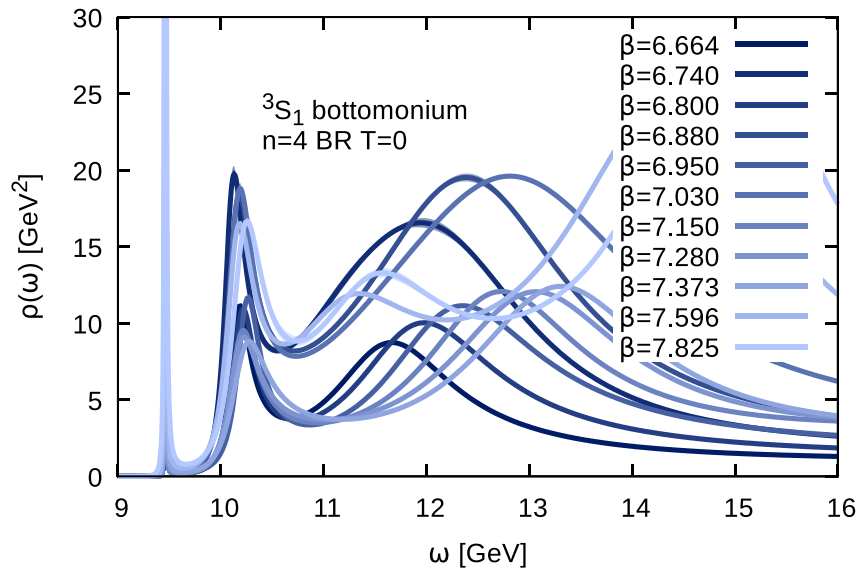
„low gain – low noise“

Calibrating the smooth BR method



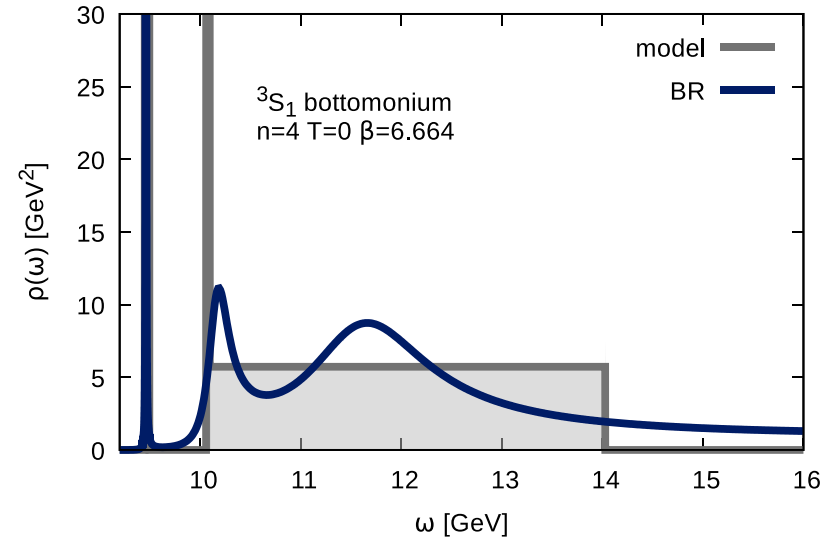
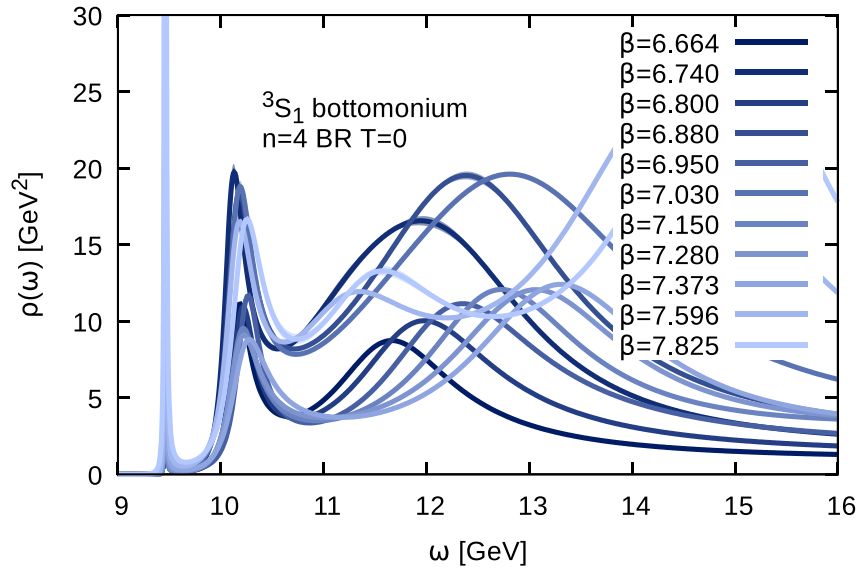
- Hyperparameter κ can be self consistently selected (MEM smoothing implicit N_T, w_{\min})
- Use prior knowledge: free spectral functions known analytically
- In reconstruction from $N_T=12$ data: $\kappa=1$ successfully suppresses ringing
- Use smooth BR to verify peak existence, standard BR for peak position etc.

Information content at $T=0$



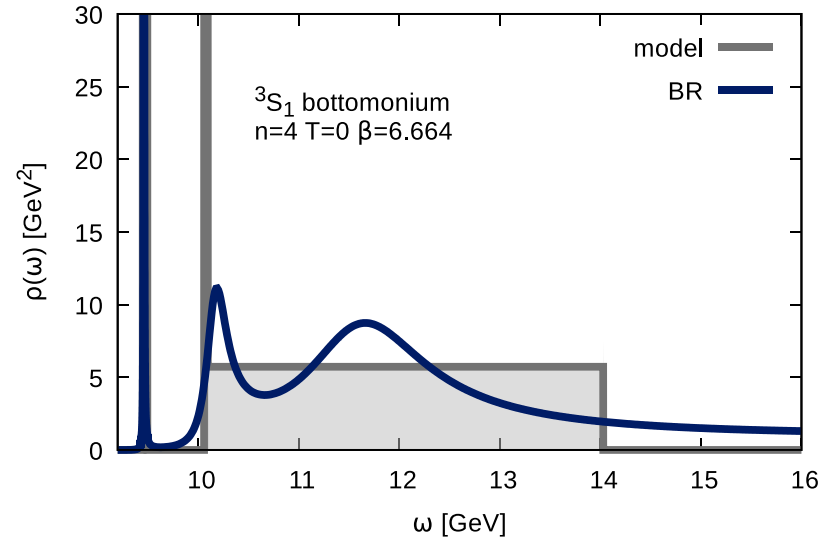
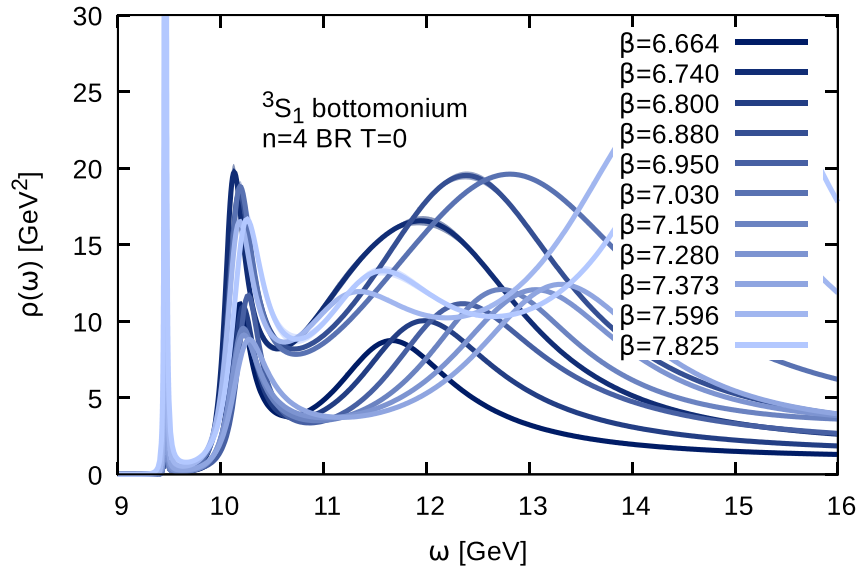
- With a hypothetically perfect extraction, how much can we learn from the data?

Information content at $T=0$

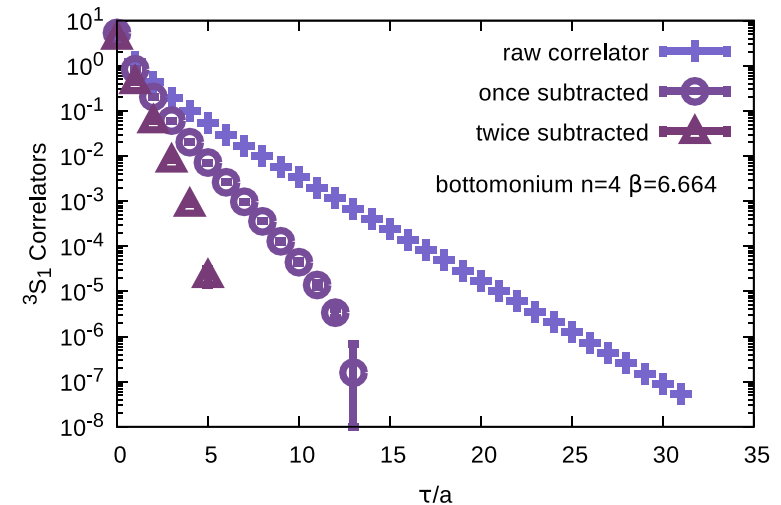


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- Offer alternative interpretation of correlator: two peaks and a box. Fits correlator $\chi^2/N_T \approx 1$

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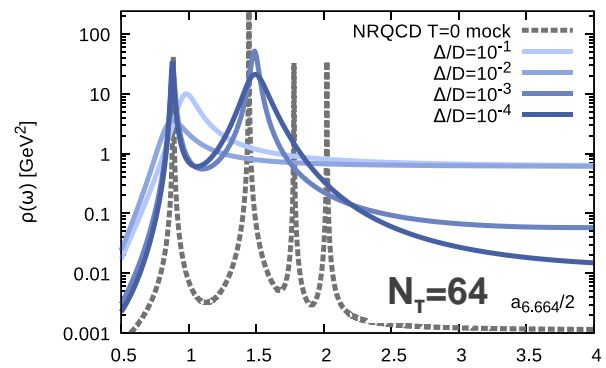
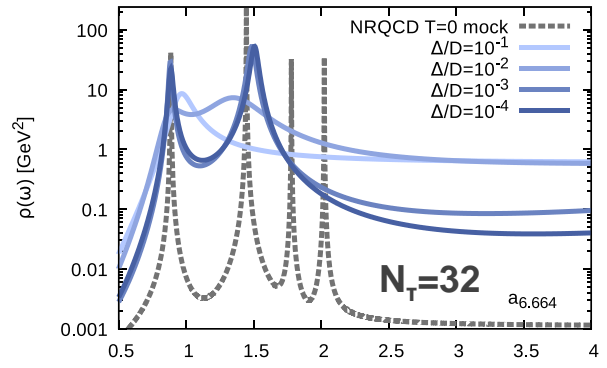


- With a hypothetically perfect extraction, how much can we learn from the data?
- Offer alternative interpretation of correlator: two peaks and a box. Fits correlator $\chi^2/N_T \approx 1$
- After subtracting two peaks, only small # of relevant points remain.



How to improve reconstructions?

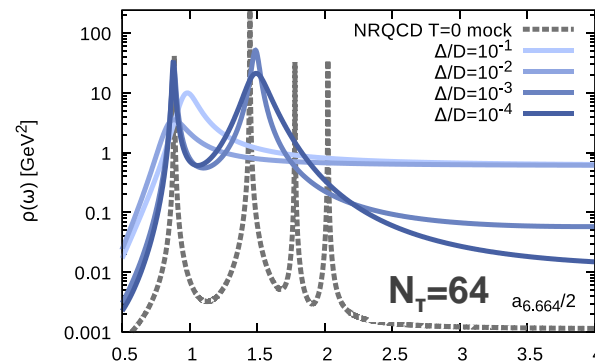
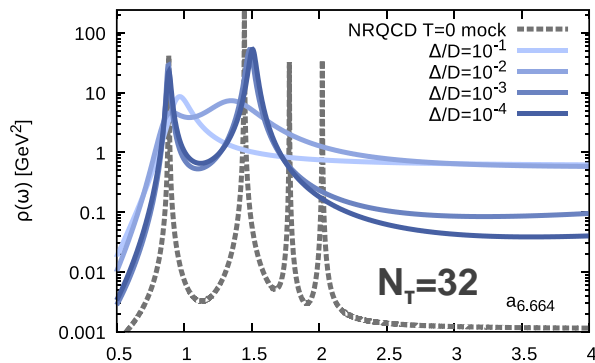
Mock Test



■ Towards the continuum: no significant improvement of bound state reconstruction

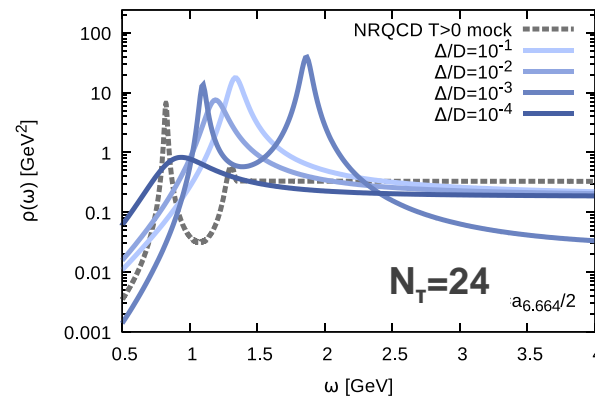
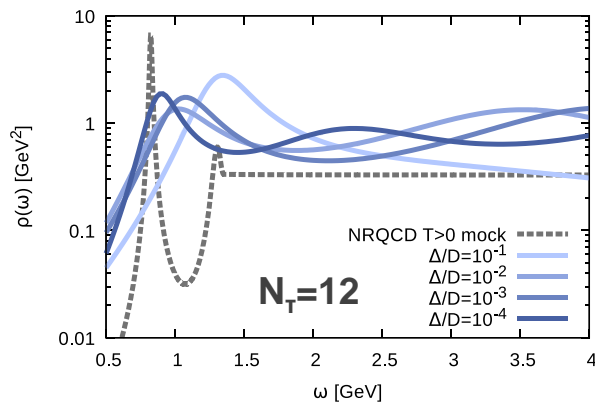
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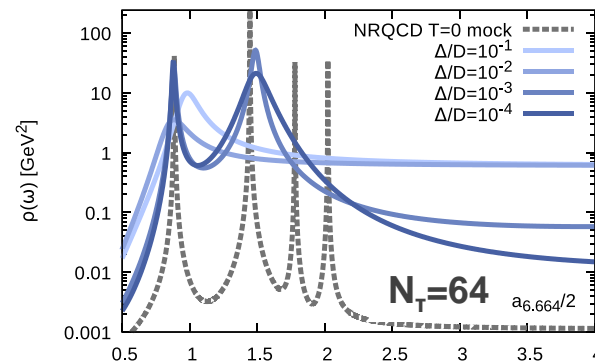
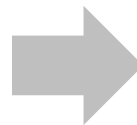
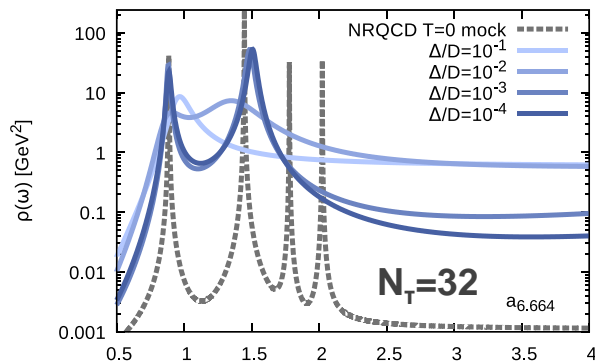
Mock Test



With e.g. anisotropic lattices, the continuum will be better under control

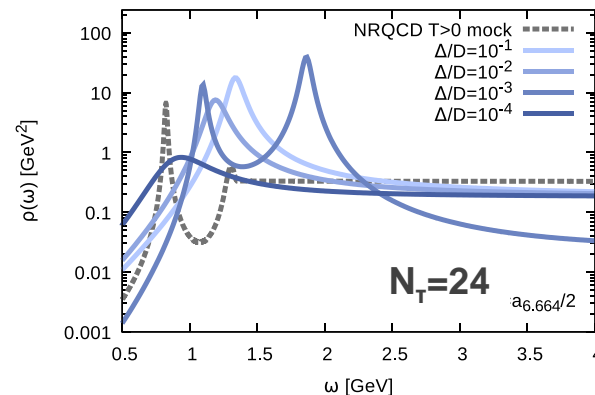
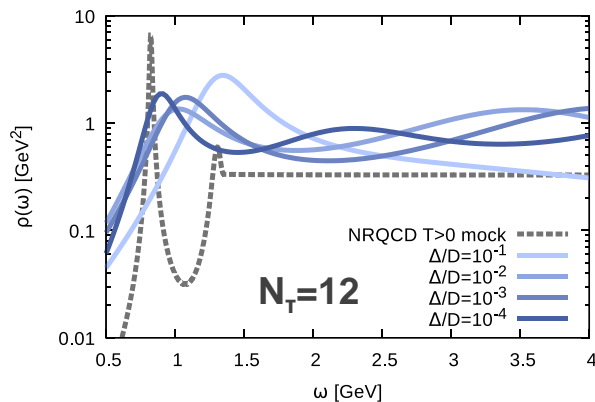
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Towards the continuum: no significant improvement of bound state reconstruction

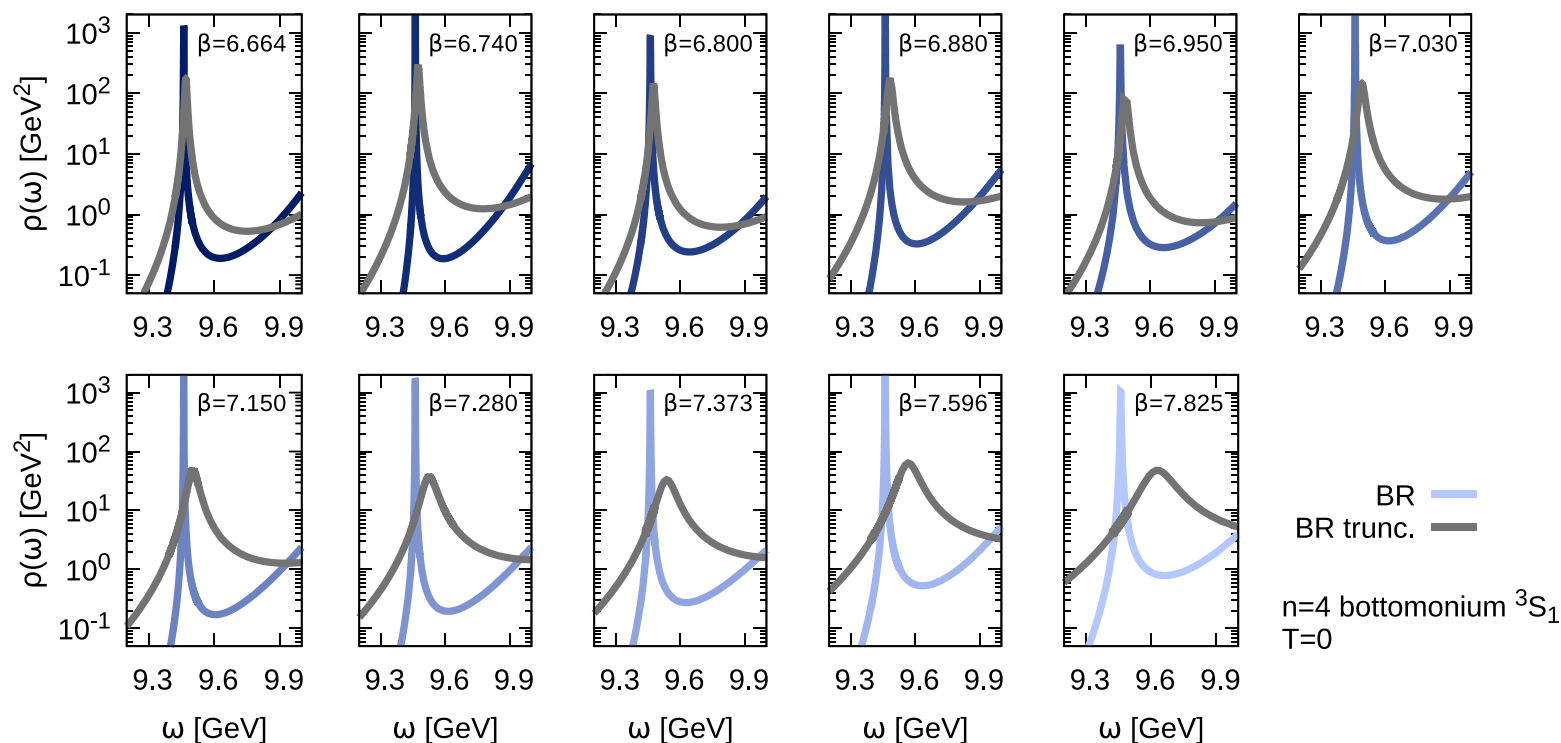
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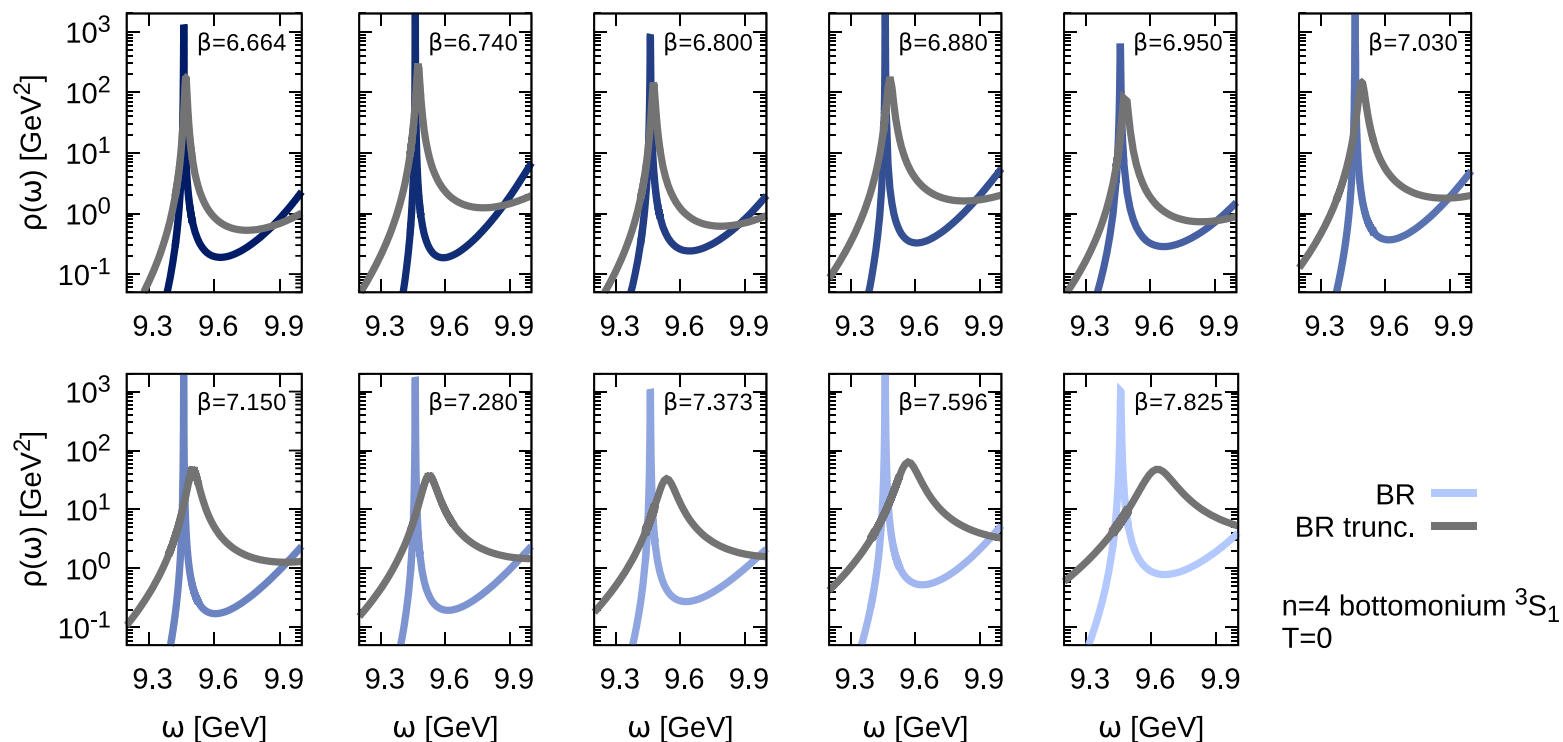
Progress needs new ideas: e.g. full QCD multilevel algorithm.

Towards finite temperature



- “High-gain” BR method resolves $T=0$ ground state very well from $N_T=48-64$ points
- How does accuracy suffer from limited Euclidean extent at $T>0$ ($N_T=12$) ?

Towards finite temperature



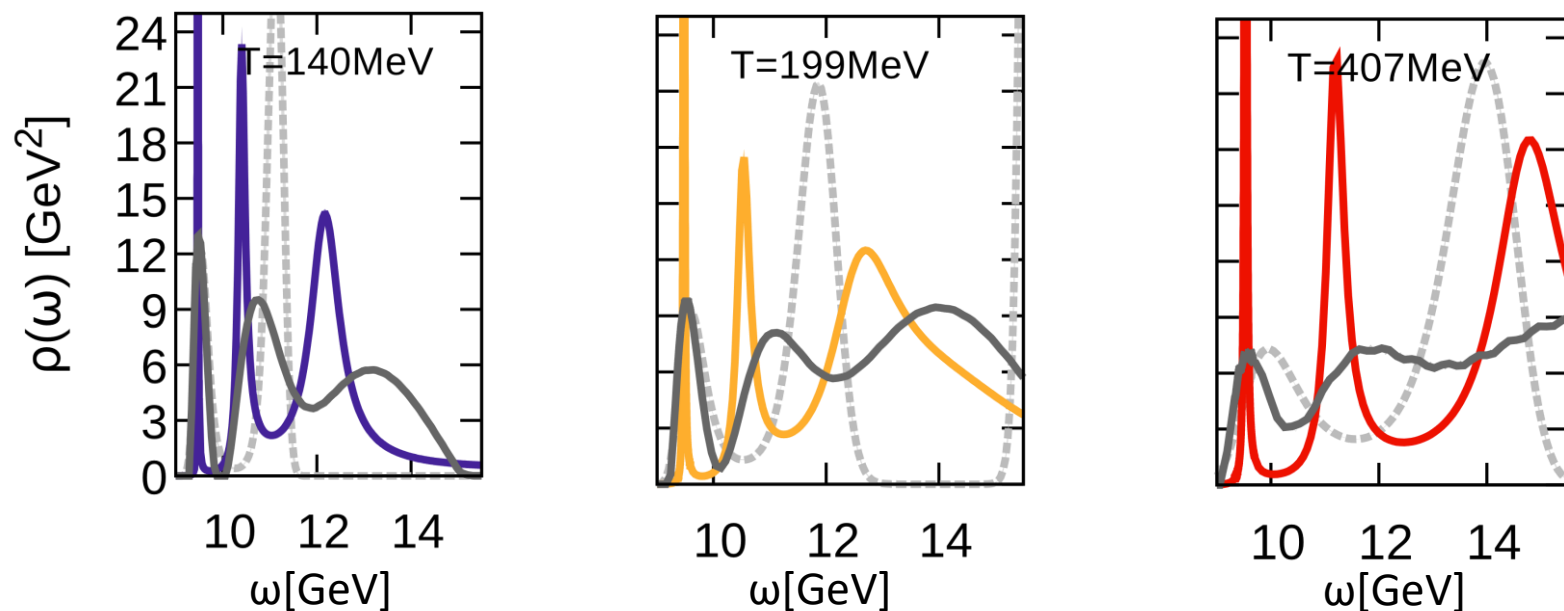
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Systematic shift of peaks to higher frequencies, as well as broadening. needs to be accounted for when analyzing $T>0$ spectra

Bottomonium S-wave at $T > 0$

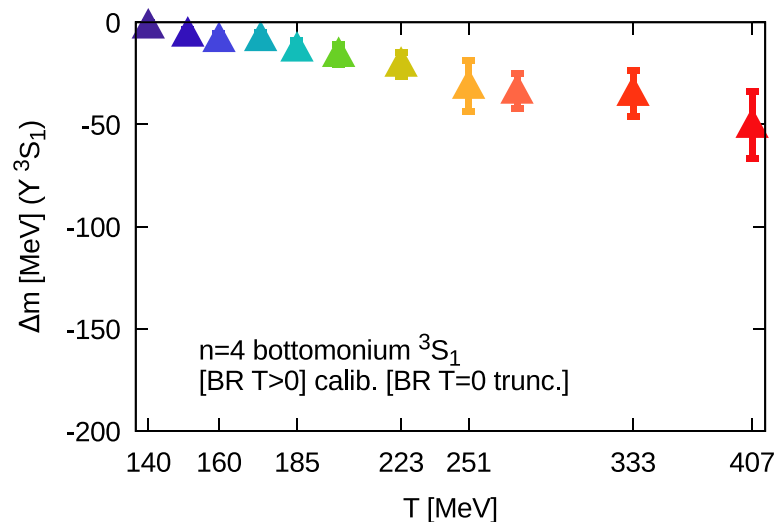
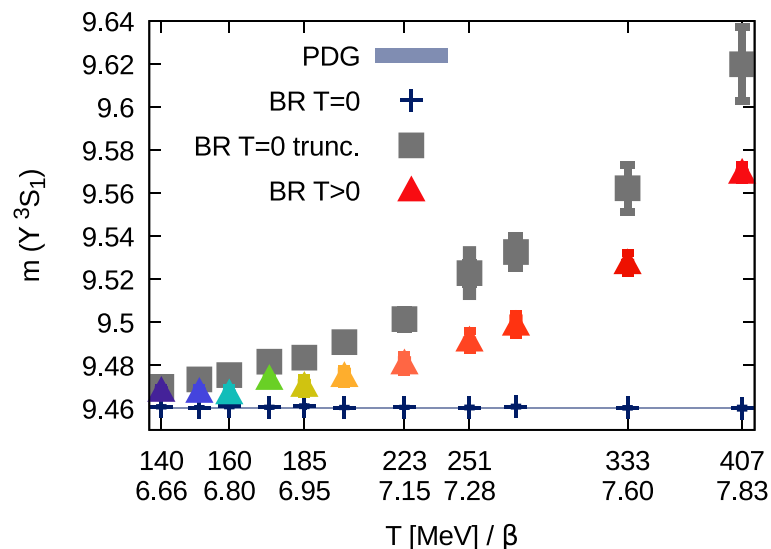
- Inspection of Upsilon (1S) ground state in medium modification



- Smooth BR method and MEM show very similar peak heights
- Peak position of original BR method and smooth BR method consistent

In-medium mass shifts

- Need to establish correct baseline to compare in-medium masses to



- Truncated T=0 reconstruction shows artificial shift to higher frequencies (gray sq.)
- In-medium shifts at T=140MeV very close to truncated results (no in-medium mod.)
- At higher temperatures masses lie clearly below the baseline (compatible with non-perturbative potential based computations (pNRQCD))

- The real-time challenge
- $T > 0$ quarkonium in-medium spectral functions on the lattice
- **Towards parton distribution functions on the lattice**
- Conclusion

The parton structure of nucleons

- Parton distribution functions: form factors of hadronic matrix elements

 $q_i(x, \mu)$

what fraction of hadron momentum x , does
the parton i carry at resolution μ [GeV]

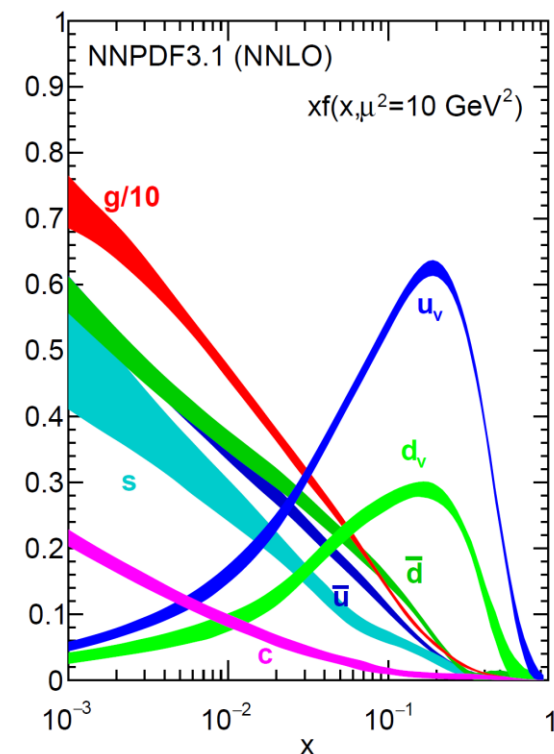
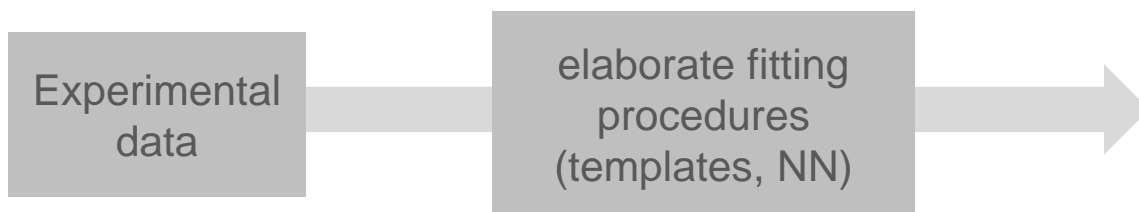
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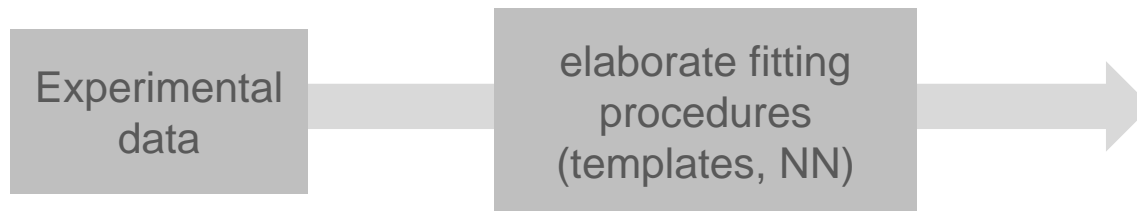
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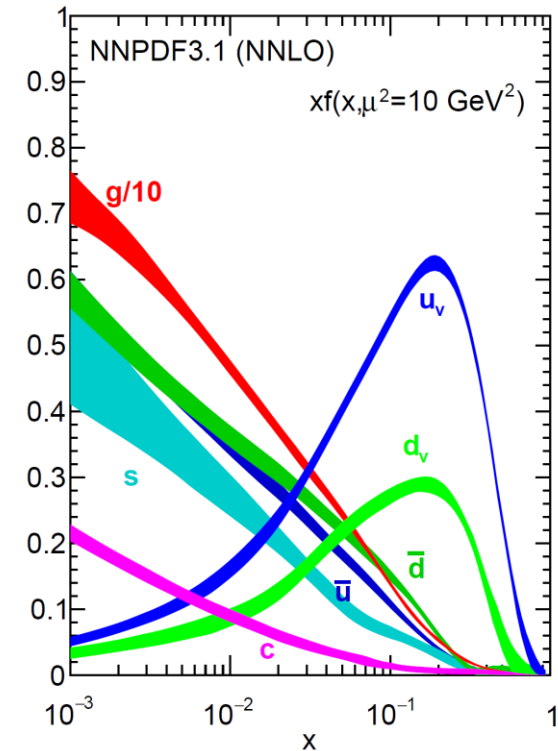
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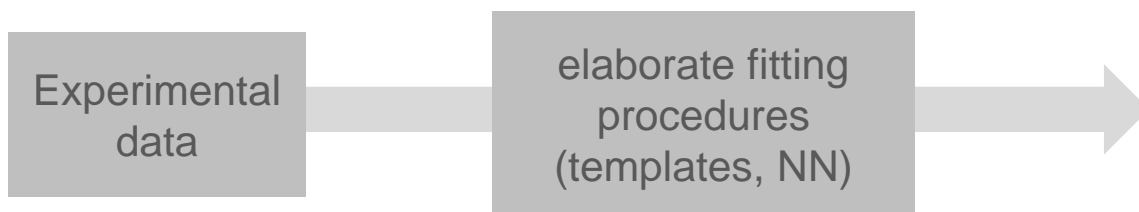
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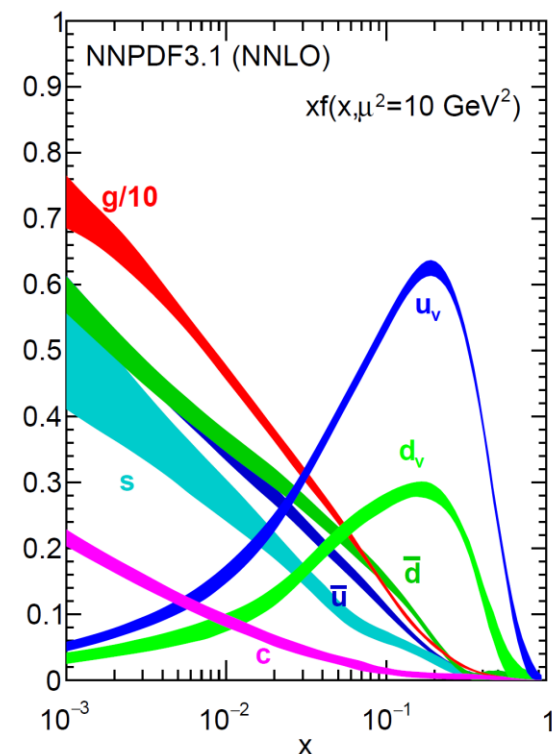
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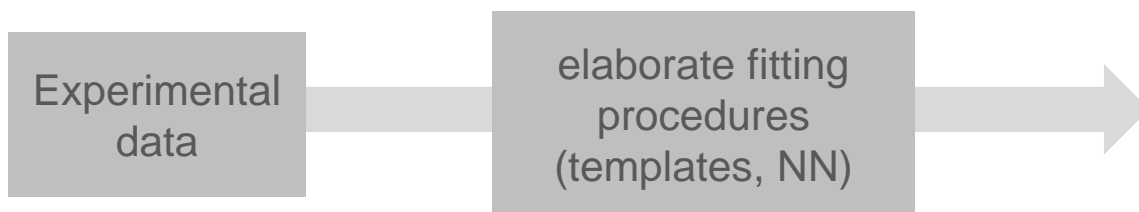
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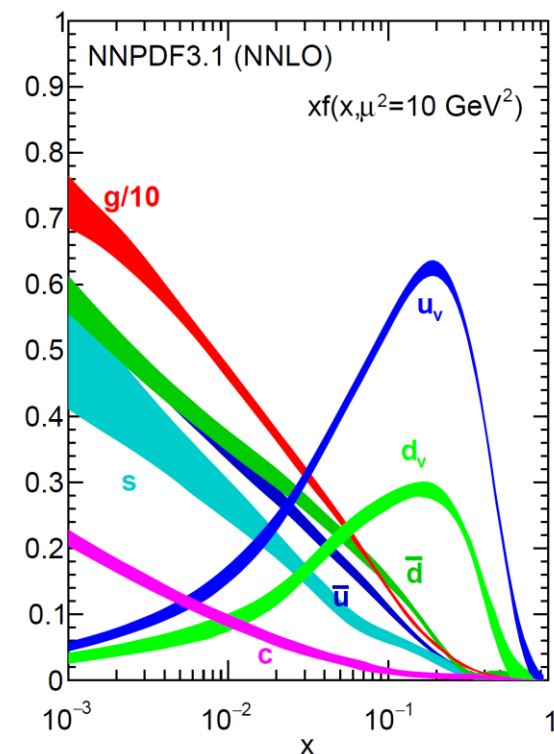
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- Theory goal: provide genuine first principles constraints to PDFs via LQCD.

Towards PDF's from the lattice

- Three strategies on the market: Quasi PDF's, Pseudo PDFs, Hadronic Tensor

Quasi PDF (Ji, 2013)

1. solve inverse problem for quasi PDF

$$M(\nu, \frac{\nu^2}{p_z^2}) = \int_0^\infty dy \cos(\nu y) \tilde{q}(y, p_z)$$

2. match result to PDF at large p_z

$$\tilde{q}(y, p_z) \longrightarrow q(x, \mu)$$

Needs 3-point function:

$$\langle H(p) | \bar{\psi}(z) \frac{\tau^3}{2} \gamma^\alpha W(z; 0) \psi(0) | H(p) \rangle = p^\alpha M(\nu, z^2) + z^\alpha N(\nu, z^2)$$

+ perturbative matching

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Pseudo PDF (Radyushkin, 2017)

1. match M to loffe time PDF Q

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Hadronic Tensor (Liu, 1994)

$$\begin{aligned} W_{\mu\nu} &= \frac{1}{4\pi} \int d^4 z e^{iqz} \langle N(p) | [J_\mu^\dagger(z), J_\nu(z)] | N(p) \rangle \\ &= \Pi_{\mu\nu}^{(1)} F(x, Q^2) + \Pi_{\mu\nu}^{(2)} F_2(x, Q^2) \end{aligned}$$

$$F_1(x, Q^2) \rightarrow q(x, Q^2) \quad F_2(x, Q^2) \rightarrow xq(x, Q^2)$$

1. Compute renormalized lattice $W_{\mu\nu}^E$
2. Analytic continuation to Minkowski

$$W_{\mu\nu}^E(\mathbf{q}, \mathbf{p}, \tau) = \int d\omega e^{-\tau\omega} W_{\mu\nu}(\mathbf{q}, \mathbf{p}, \omega)$$

Requires computation
of 4-point function

The pseudo PDF inverse problem

- Ill-posed inverse problem due to interplay of finite v and limited integration range

$$Q(\nu, \mu) = \int_0^1 dx \cos(\nu x) q(x, \mu) \xrightarrow[\text{datapoint } v=[0, v_{\max}]]{\text{discretize with } N_v} \mathbf{Q} = \mathbf{K} \mathbf{q}$$

- Only if $v_{\max} = 2\pi N_v$ the integral reduces to a well conditioned DFT: unrealistic on the lattice

The pseudo PDF inverse problem

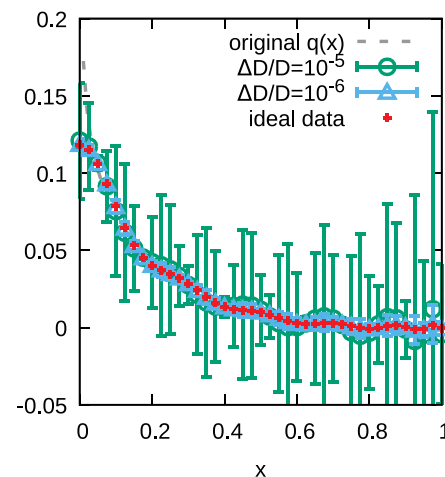
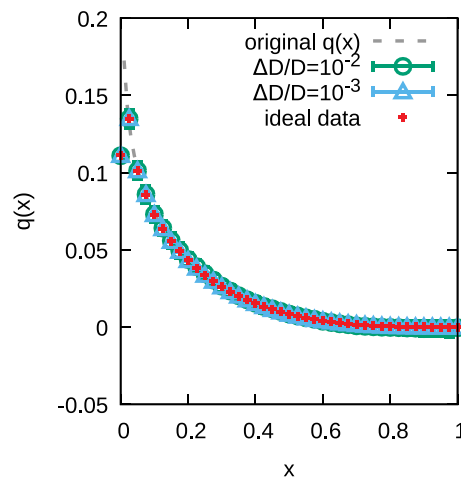
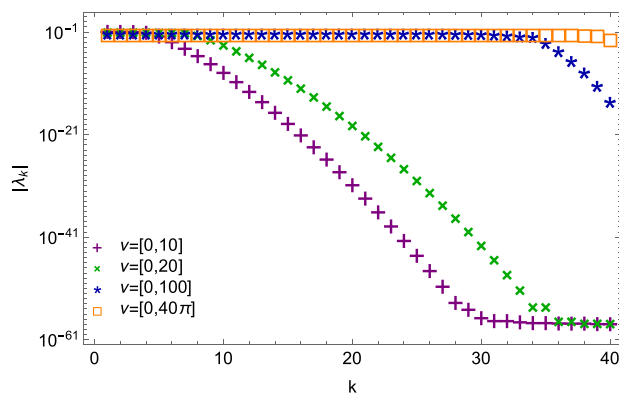
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$$Q = Kq$$

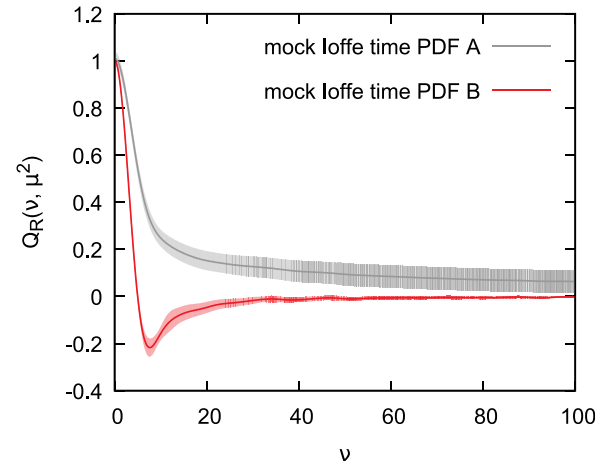
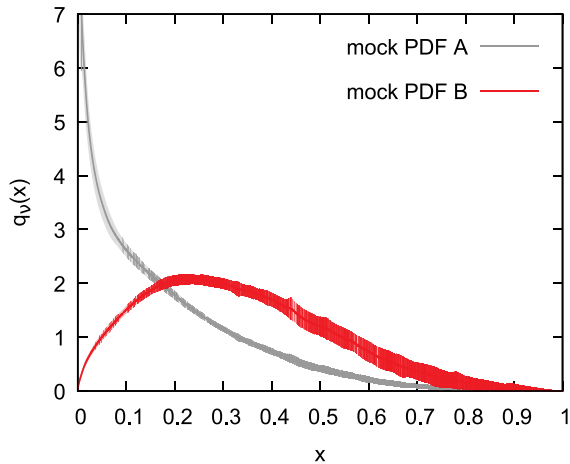
- Only if $\nu_{\max} = 2\pi N_\nu$ the integral reduces to a well conditioned DFT: unrealistic on the lattice
- Direct reconstructions are challenged: (e.g. SVD regularization for K^{-1})



- For realistic $\nu_{\max} \sim 20$ direct inversion even with 10^{-5} relative error not robust

More advanced reconstructions

- Our goal: identify most promising reconstruction approach via mock tests

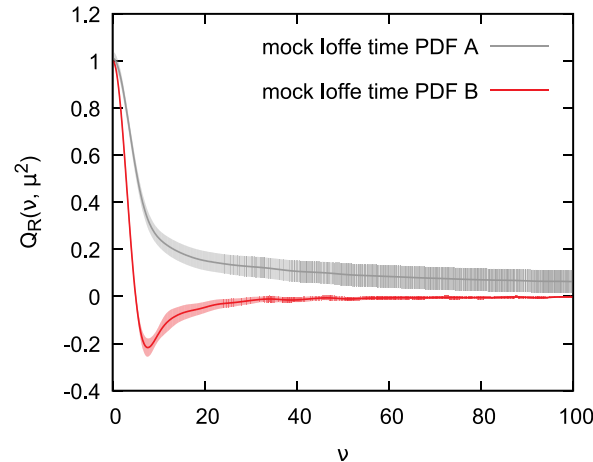
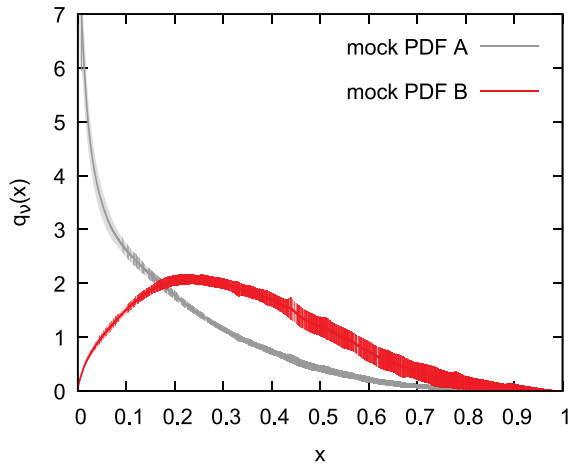


input data: 100 replicas of
 - NNPDF pheno PDF **(A)**
 - $q(x=0)=0$ deformed version **(B)**

for realistic conditions discretize
 via $\nu_{\max} \leq 20$, $N_\nu = 10-20$

More advanced reconstructions

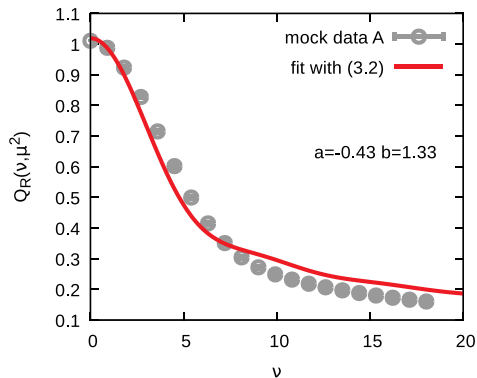
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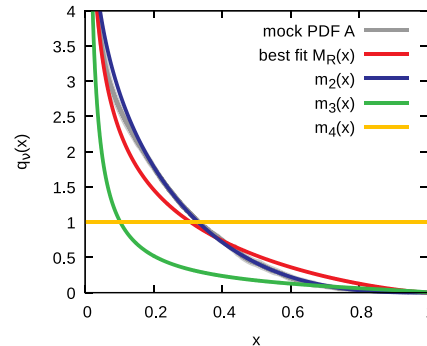
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- Prior knowledge on singularities needed for accurate reconstruction: fit Q with pheno ansatz

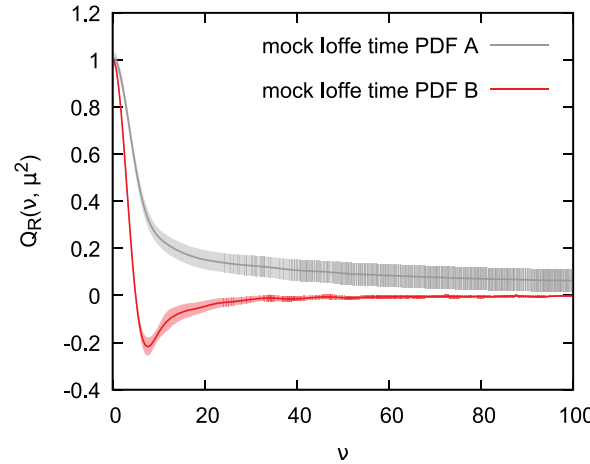
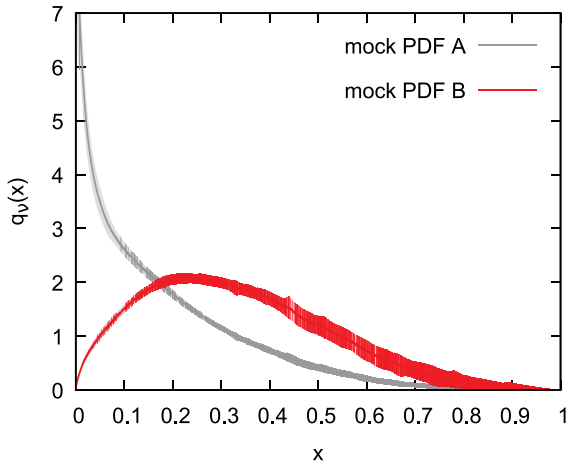


$$p(x) = x^a(x-1)^b$$



More advanced reconstructions

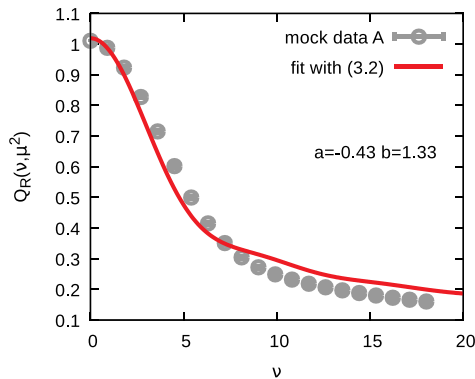
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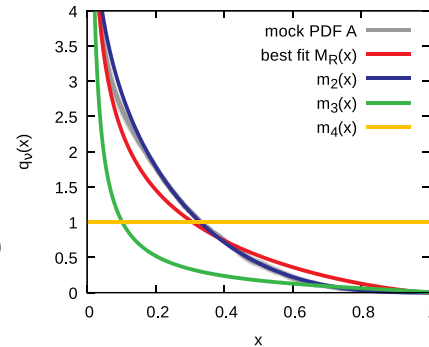
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Prior knowledge on singularities needed for accurate reconstruction: fit Q with pheno ansatz



$$p(x) = x^a(x-1)^b$$



for Backus Gilbert precondition with best polynomial fit (incorporate divergence at $x=0$):

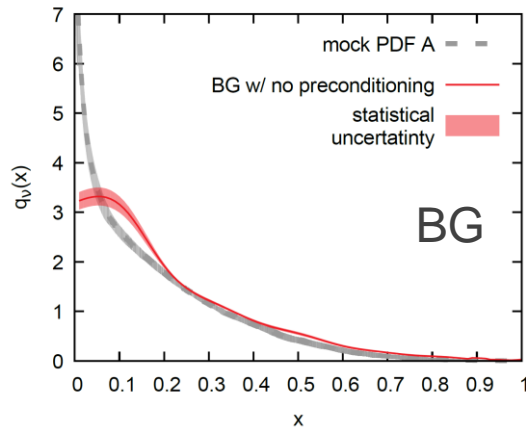
$$Q(\nu, \mu) = \int_0^1 dx \cos(\nu x) p(x) \frac{q(x, z^2)}{p(x)}$$

for Bayesian methods supply best polynomial fit as default model

$$m(x) = p(x)$$

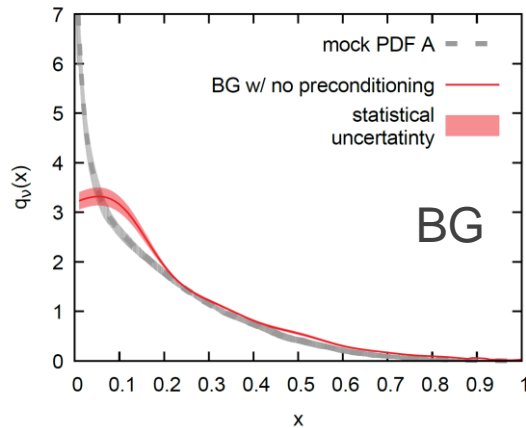
Comparison of approaches (A)

- Test battery BG – MEM – BR – Tikhonov, based on $v_{\max} = 10$, $N_v = 12$



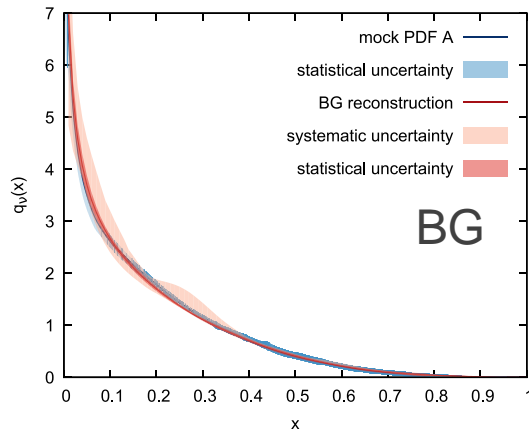
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- Test battery BG – MEM – BR – Tikhonov, based on $v_{\max} = 10$, $N_v = 12$
- fitted $p(x)$ captures PDF well: methods incorporating $m=p$ strongly in end result at advantage



Comparison of approaches (A)

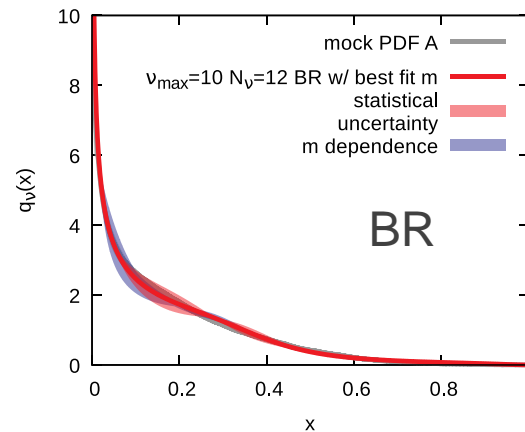
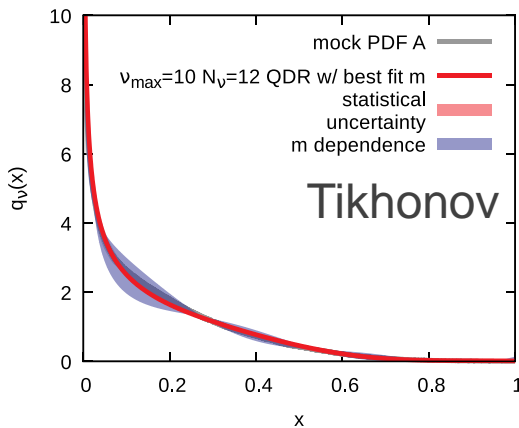
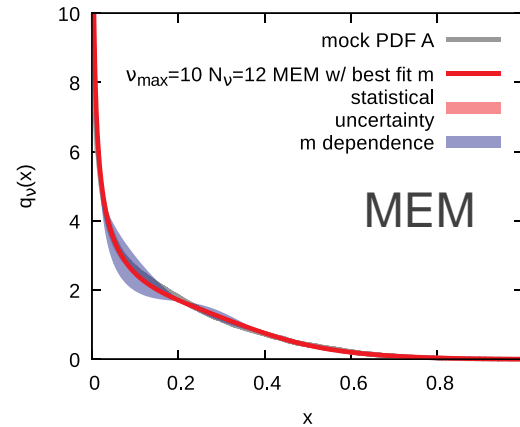
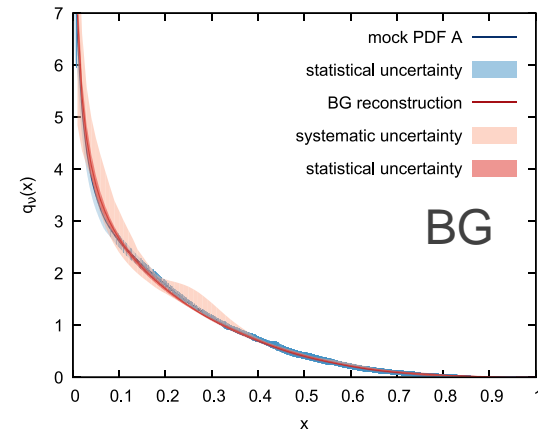
- Test battery BG – MEM – BR – Tickhonov, based on $v_{\max} = 10$, $N_v = 12$
- fitted $p(x)$ captures PDF well: methods incorporating $m=p$ strongly in end result at advantage



Comparison of approaches (A)

Test battery BG – MEM – BR – Tikhonov, based on $v_{\max} = 10$, $N_v = 12$

fitted $p(x)$ captures PDF well: methods incorporating $m=p$ strongly in end result at advantage



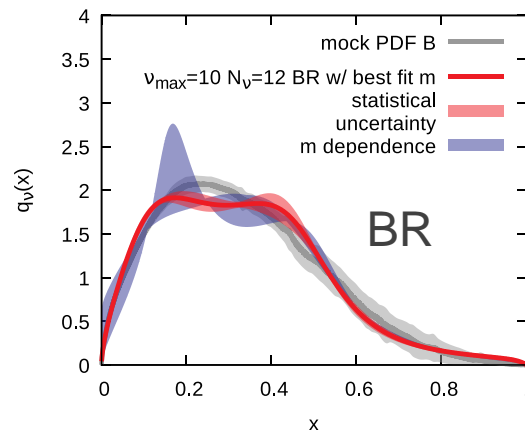
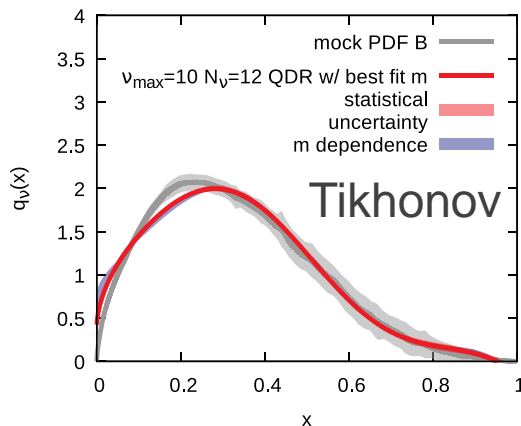
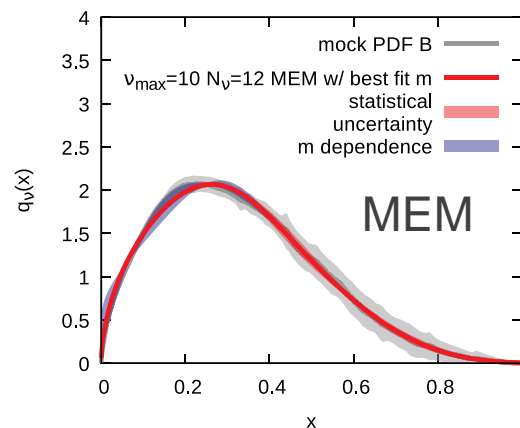
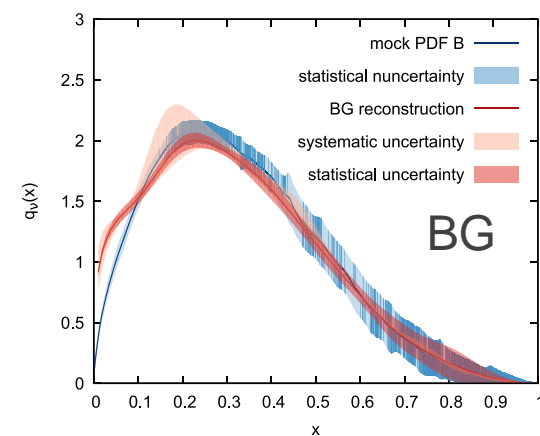
Similar performance among all methods for scenario (A) if prior information in $q(x \rightarrow 0)$ present

Systematic errors from changing the preconditioning polynomial (fit parameters x^2 or $x^{0.5}$)

Comparison of approaches (B)

Test battery BG – MEM – BR – Tikhonov, based on $v_{\max} = 10$, $N_v = 12$

fitted $p(x)$ captures PDF well: methods incorporating $m=p$ strongly in end result at advantage



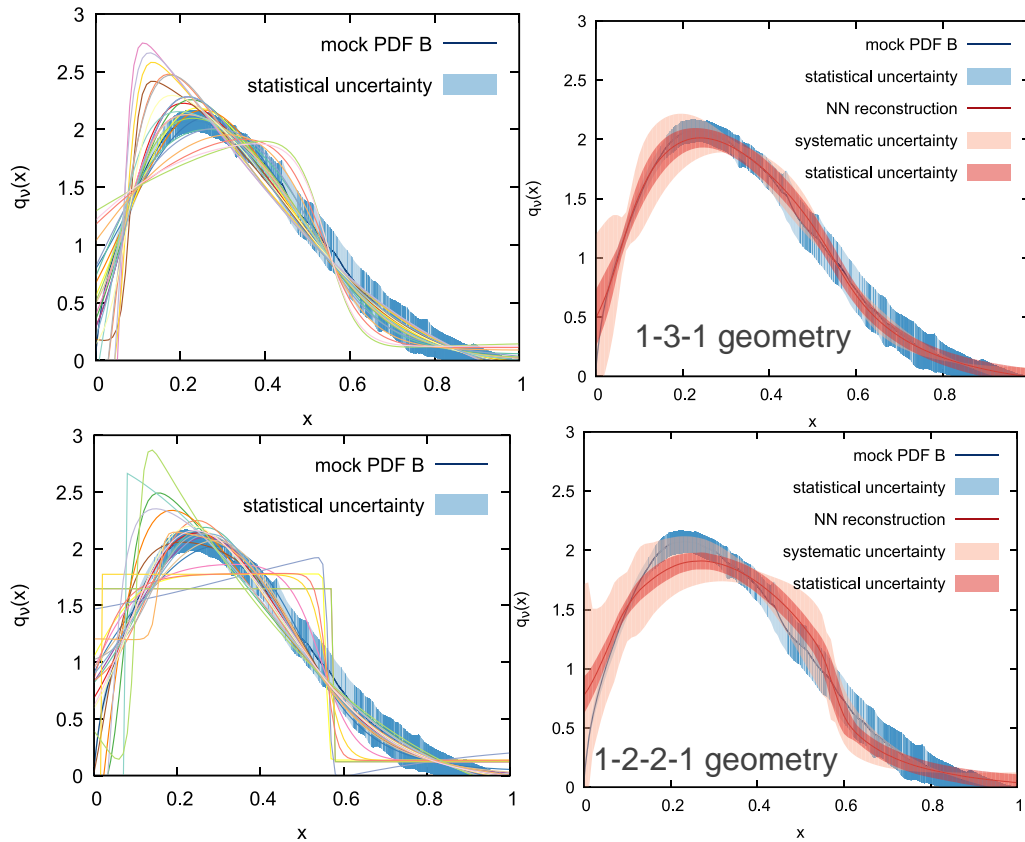
MEM most accurate and precise for scenario (B), BG and Tikhonov struggle with $q(0)=0$.

Systematic errors from changing the preconditioning polynomial (fit parameters x^2 or $x^{0.5}$)

Extending input data to $v_{\max} = 20$, $N_v = 24$ leads to sign. improved results and all Bayesian methods comparable

Neural network approach

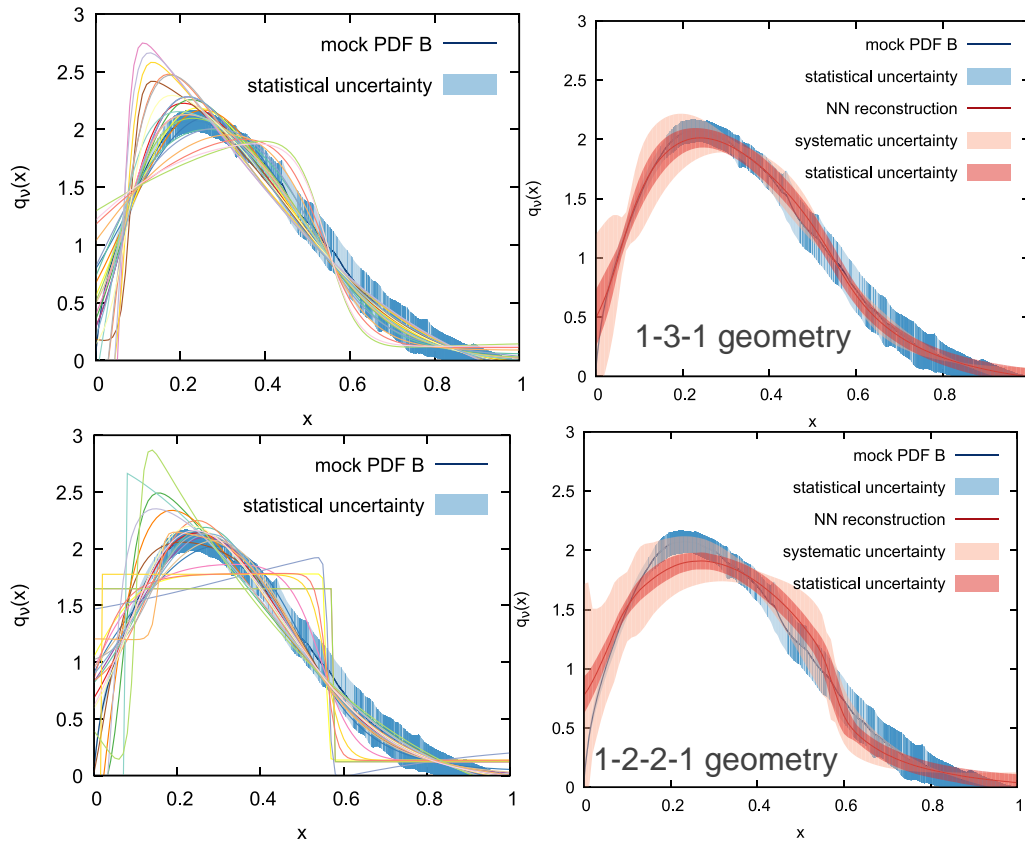
- Current interpretation: sampling of degenerate χ^2 functional with restricted basis



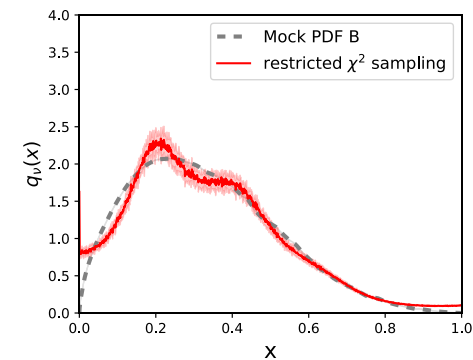
- Use genetic algorithm (sim. annealing) on average of 100 replicas to generate a set of 25 optimal NNs: variation as systematic uncertainty
- Generate optimal NN for each of the 100 replicas: variation as statistical uncertainty

Neural network approach

- Current interpretation: sampling of degenerate χ^2 functional with restricted basis

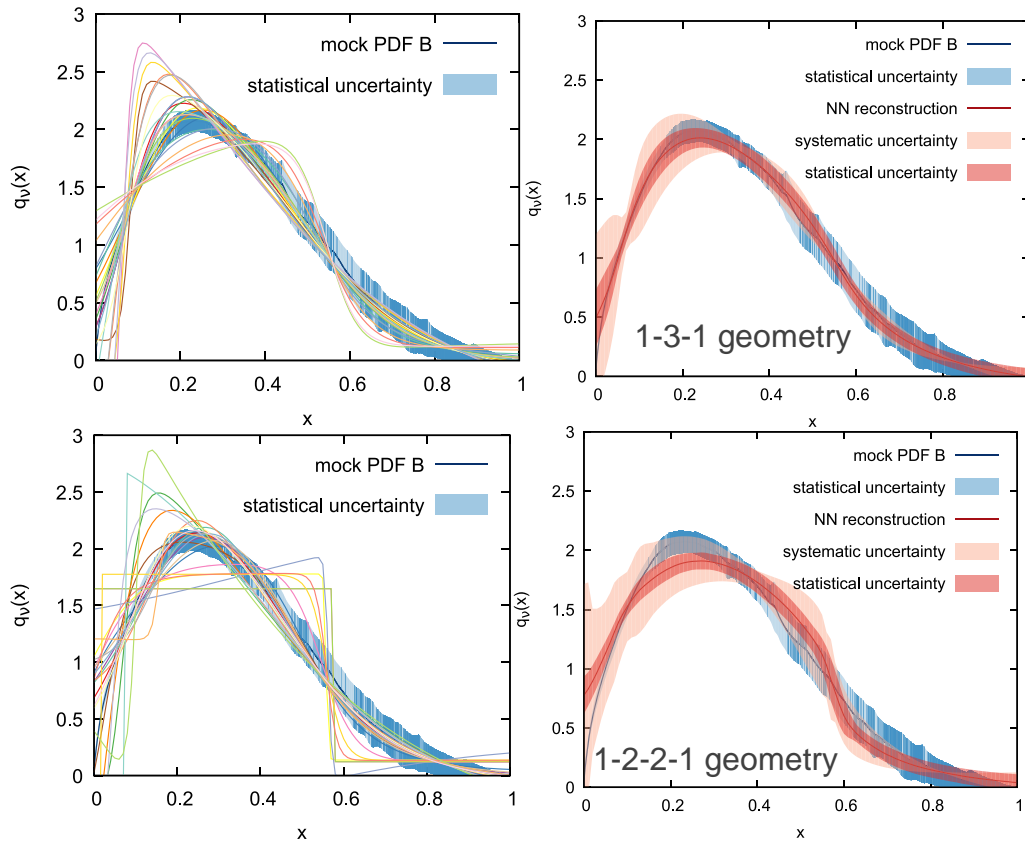


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- 1-3-1 geometry improves on naïve sampling of χ^2 functional with $q > 0$

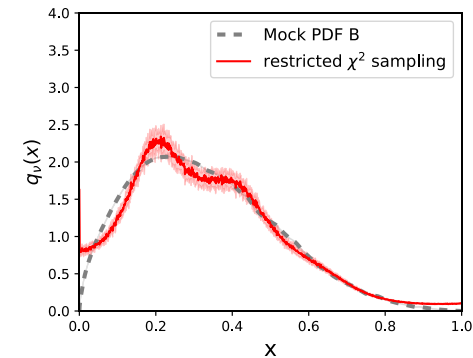


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- 1-3-1 geometry improves on naïve sampling of χ^2 functional with $q > 0$



- Need to better understand influence of NN geometry on end result, systematic not quantified

- The real-time challenge
- $T > 0$ quarkonium in-medium spectral functions on the lattice
- Towards parton distribution functions on the lattice
- **Conclusion**

Conclusion

- Physics of HIC urges non-perturbative understanding of QCD real-time dynamics
- Lattice QCD real-time information hidden behind ill-posed inverse problems
 - Main challenges: **exponential information loss** and **limited Euclidean time extent**
- Two concrete examples of recent progress:
 - **In-medium heavy quarkonium** spectral functions: new estimate for in-medium mass shifts from a better understanding of reconstruction systematics
 - **Parton Distribution Functions**: first step beyond naïve inversions. Promising for accurate extraction of PDFs directly from upcoming lattice QCD simulations

Conclusion

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 - **Parton Distribution Functions**: first step beyond naïve inversions. Promising for accurate extraction of PDFs directly from upcoming lattice QCD simulations
- A lot of work remains to be done:
 - **Improving Bayesian methods**: need to incorporate more specific prior information
 - **Improve understanding of NN reconstruction**: e.g. influence of NN geometry

Backup slides

Non Bayesian approaches

Projection methods: Pade, Cuniberti

Find “optimal” approximation to the Matsubara correlator $D(\omega_n)$

$$C(\omega) = \frac{z_0}{1 + \frac{z_1(\omega - \omega_1)}{1 + \frac{z_2(\omega - \omega_2)}{\vdots}}}$$

z_i chosen such that $C(\omega_n) = D(\omega_n)$

Corresponds to a projection onto rational basis functions

Spectral functions from analytic continuation $\text{Im}[C(i\omega)]$

No default model, but requires very small statistical errors. Also reconstruction does not necessarily respect spectral rep.

Backus-Gilbert Method

Attempt to simplify the problem as far as possible by linear combinations of input data:

$$\begin{aligned} \tilde{D}(\tau') &= \int d\tau \Sigma(\tau', \tau) D(\tau) \\ &= \int d\omega \int d\tau \Sigma(\tau', \tau) K(\omega, \tau) \rho(\omega) \end{aligned}$$

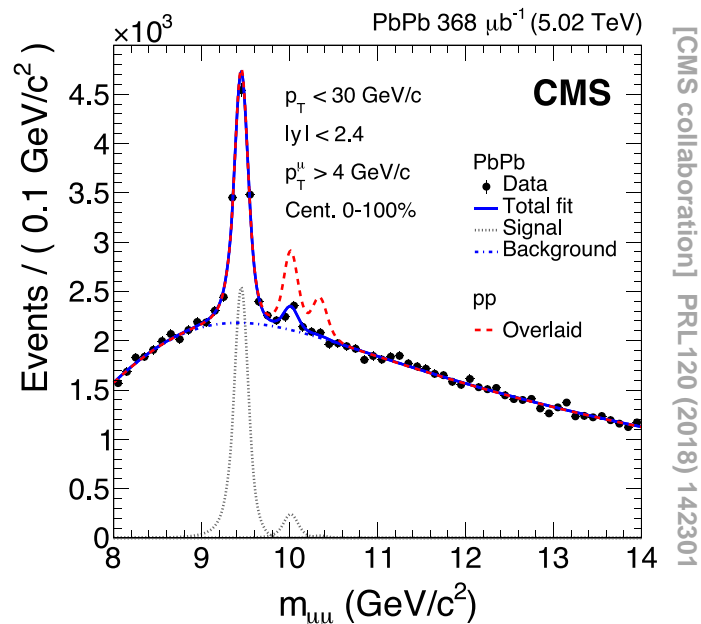
Goal: construct a resolution function

$$\int d\tau \Sigma(\tau', \tau) K(\omega, \tau) \approx \delta(\tau' - \omega)$$

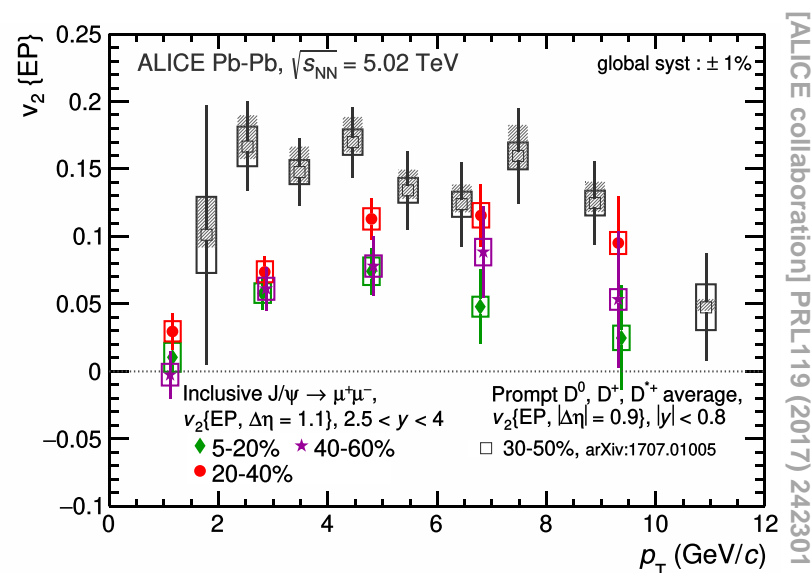
No default model dependence, but also requires a choice of regularization at intermediate steps

Motivation: Quarkonium in HIC

Heavy quarkonium: Precision probes of the QGP



Bottomonium: a non-equilibrium probe of the full QGP evolution



Charmonium: a partially equilibrated probe, sensitive to the late stages

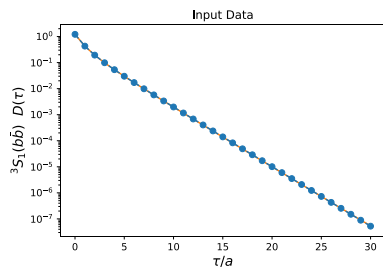
Idealized setting: properties of quarkonium in a static medium?

Towards a modern Bayesian approach

- Elevate to a full Bayesian analysis: sample the posterior via Monte Carlo
 - Much better control over both statistical and systematic uncertainties
 - Self consistent treatment of e.g. weight α possible, no ad-hoc assumptions needed

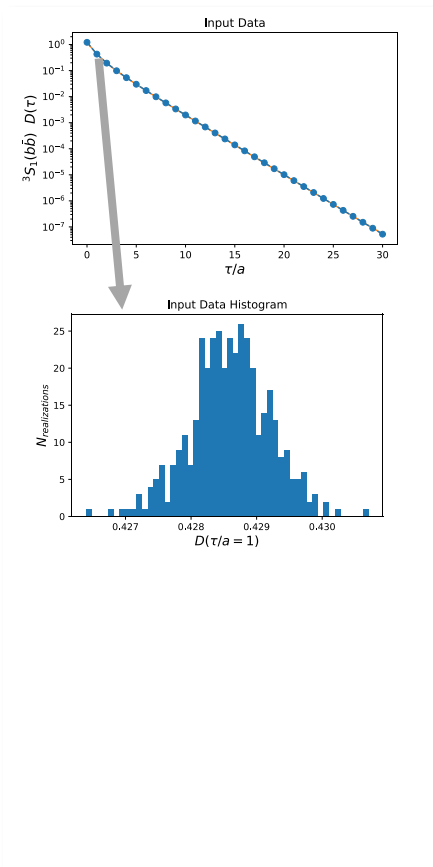
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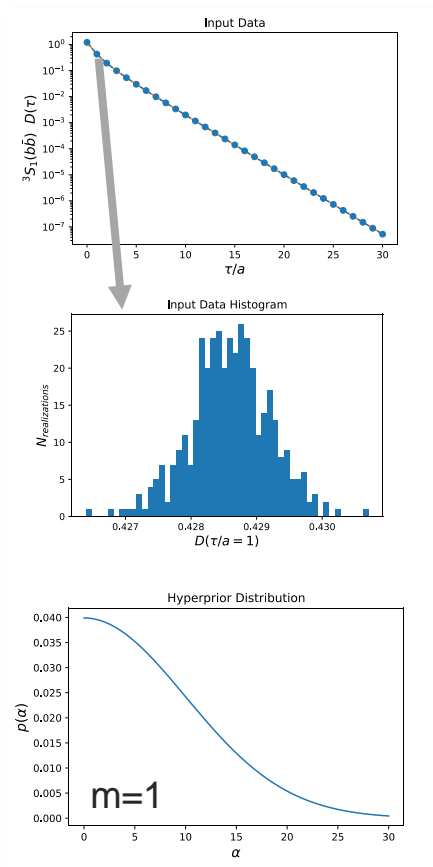
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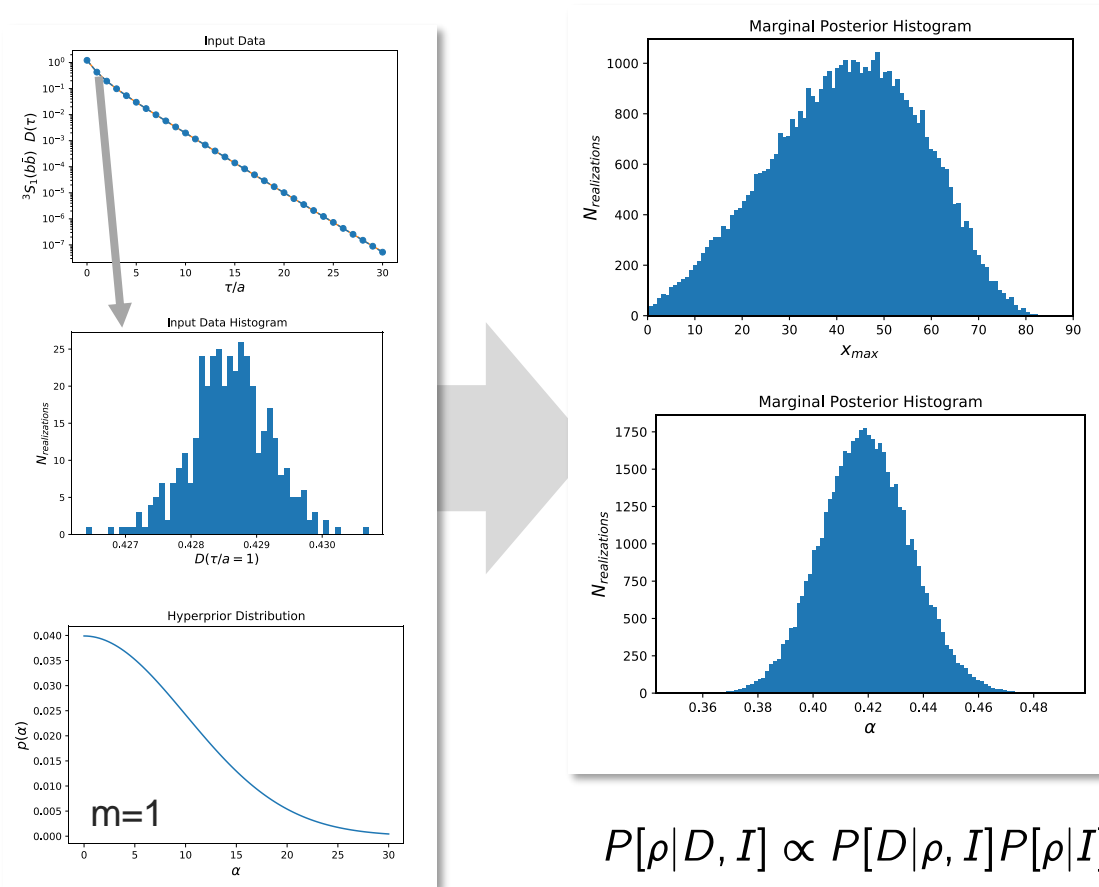
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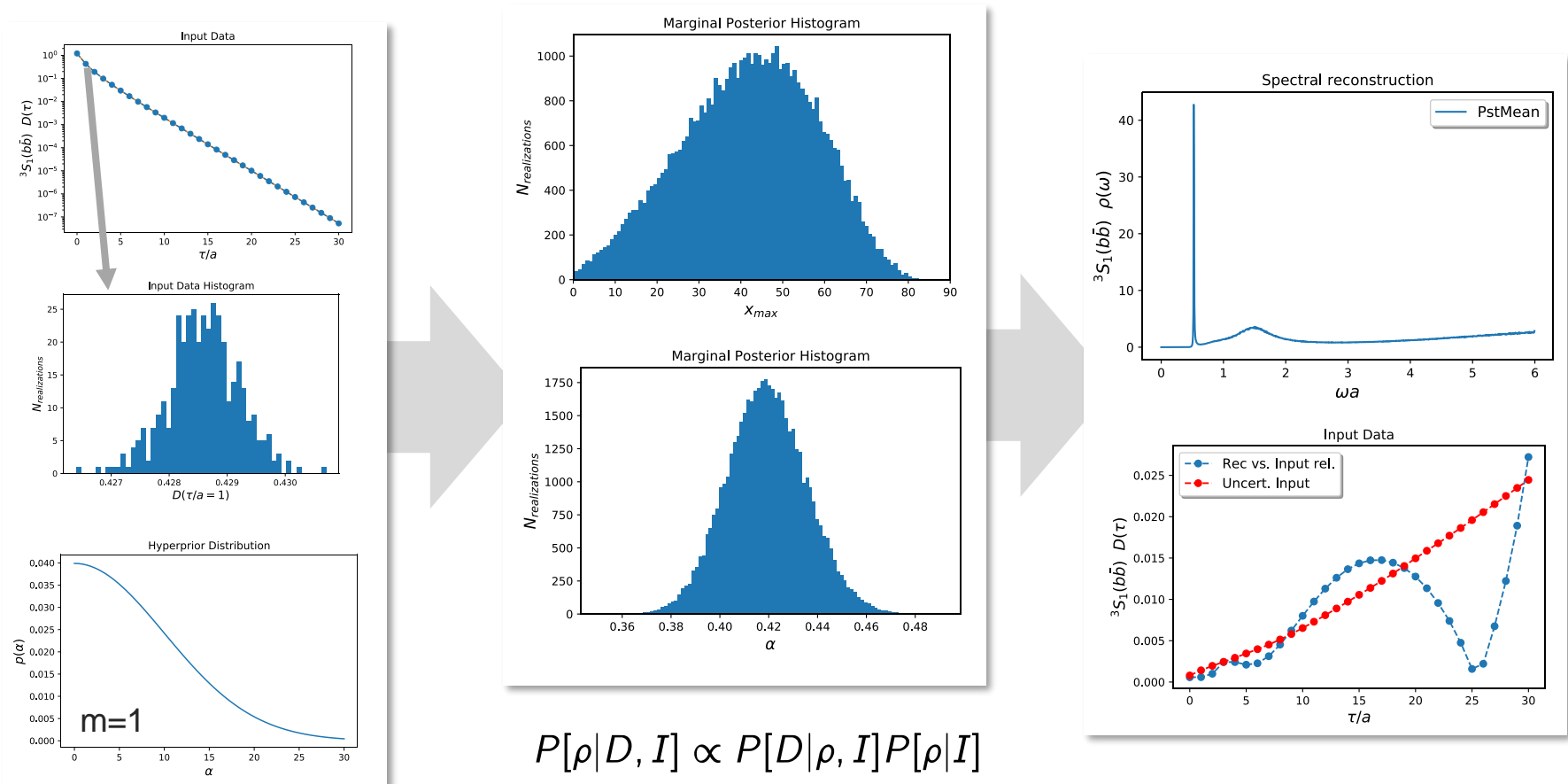
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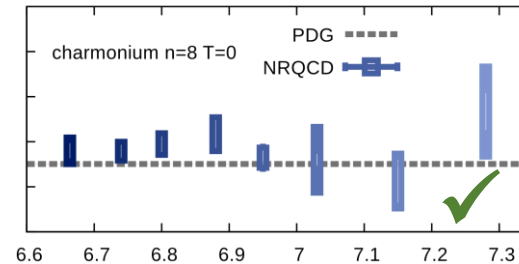
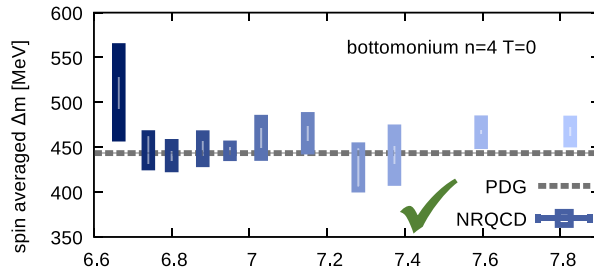
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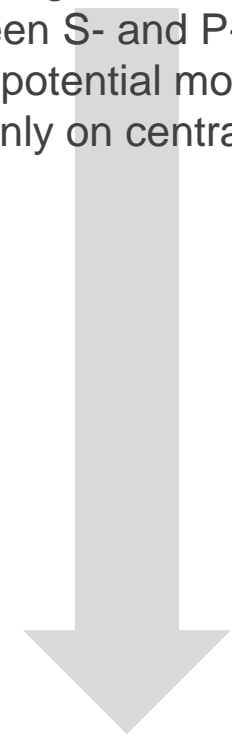


Mass splittings at $T=0$

- With $T>0$ spectra goal, no $T=0$ specific NRQCD improvements: Accuracy?

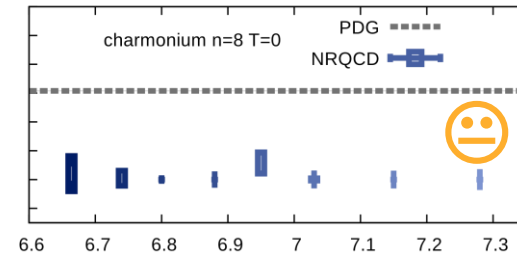
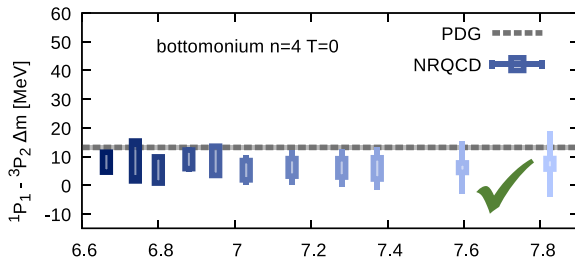
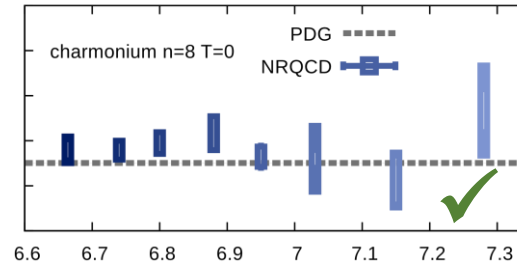
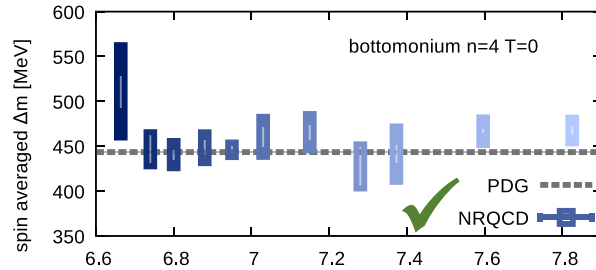


Spin weighted difference
between S- and P-wave
(c.f. potential model:
dep. only on central pot.)



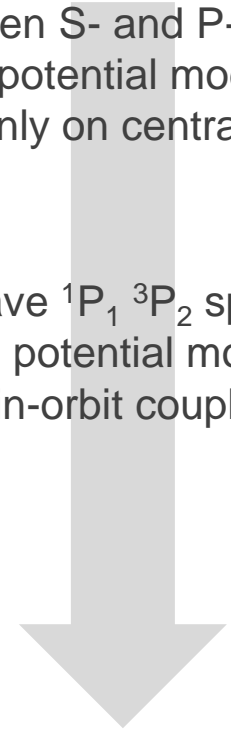
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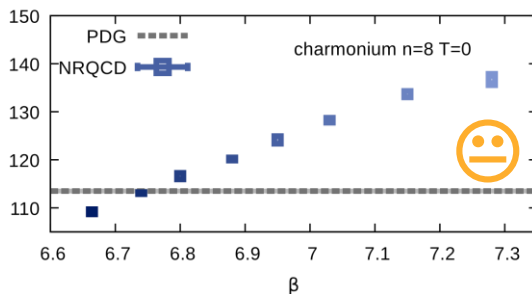
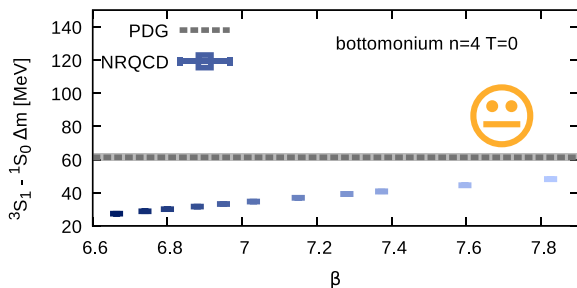
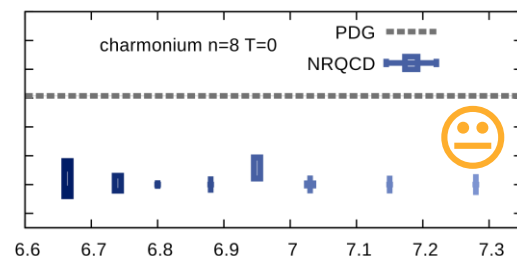
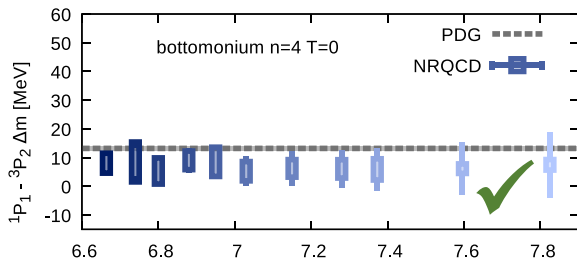
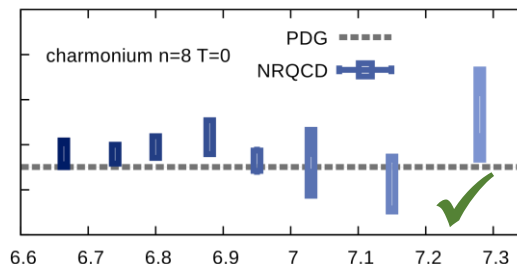
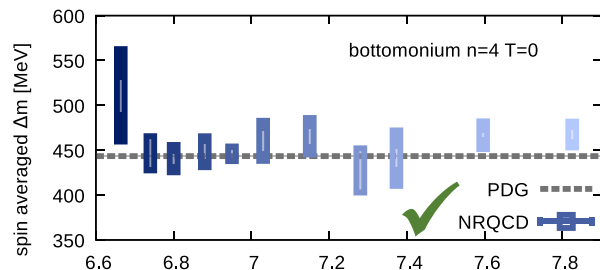
Spin weighted difference between S- and P-wave (c.f. potential model: dep. only on central pot.)

P-wave 1P_1 3P_2 splitting (c.f. potential model: spin-orbit coupling)



Mass splittings at T=0

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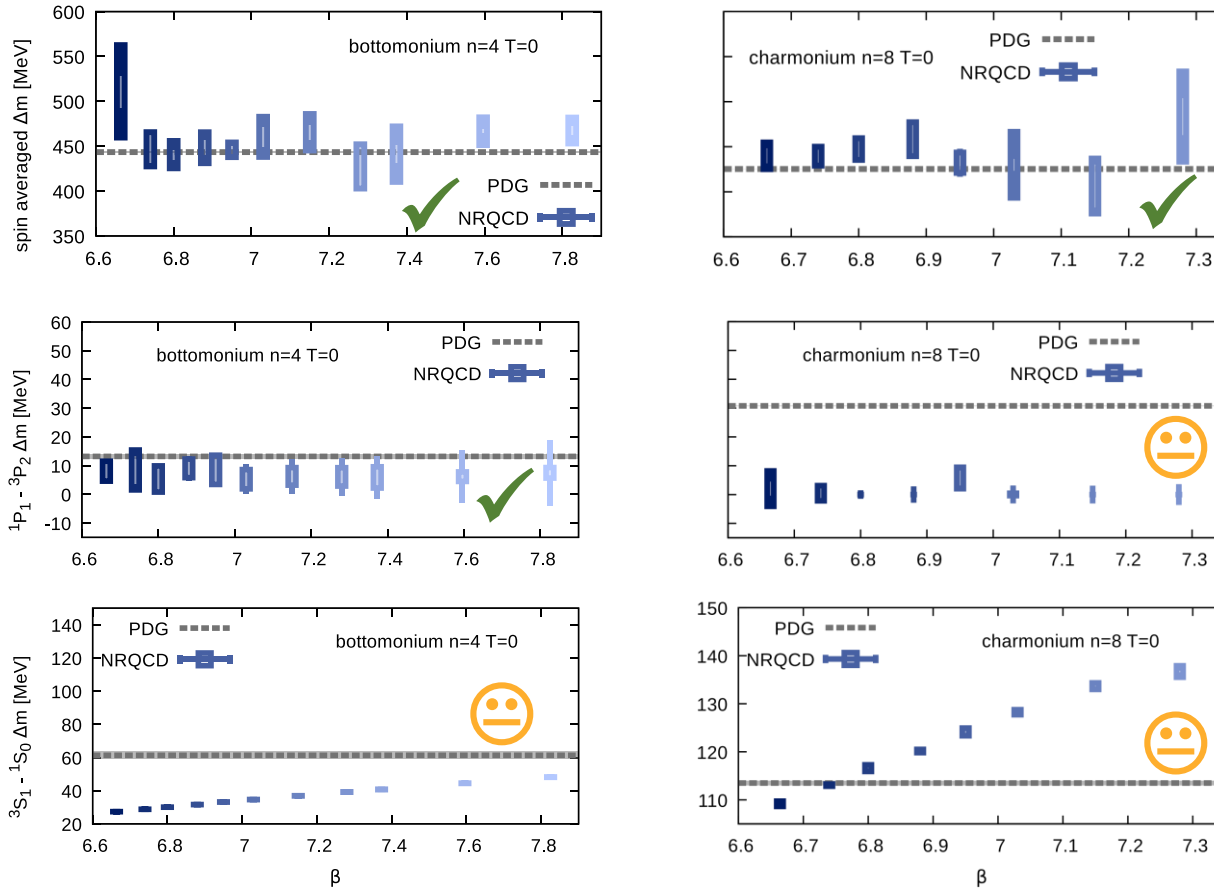
P-wave 1P_1 3P_2 splitting (c.f. potential model: spin-orbit coupling)

S-wave splitting (c.f. potential model: HFS)

Max 35MeV deviation. (HFS: NRQCD $O(v^6)$ and $O(\alpha_S v^4)$)

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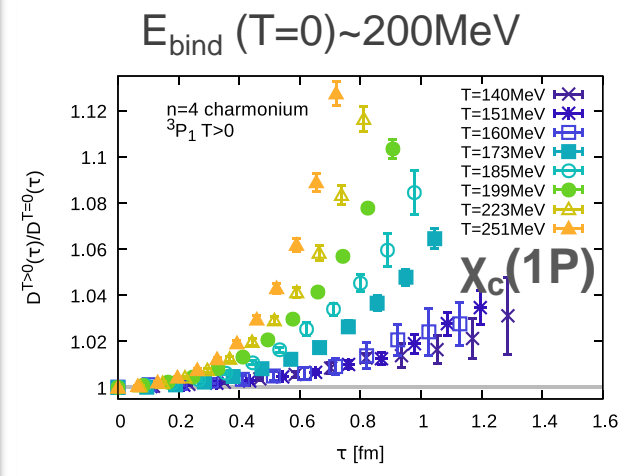
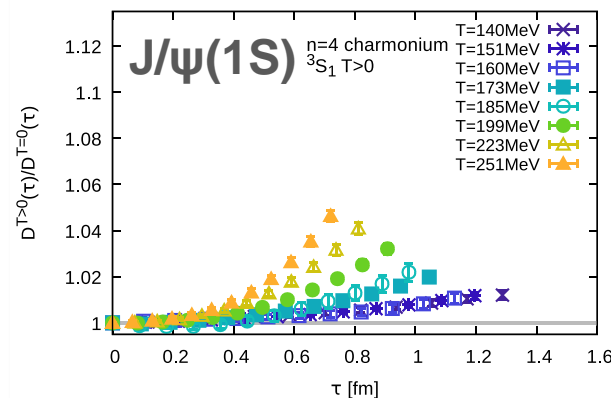
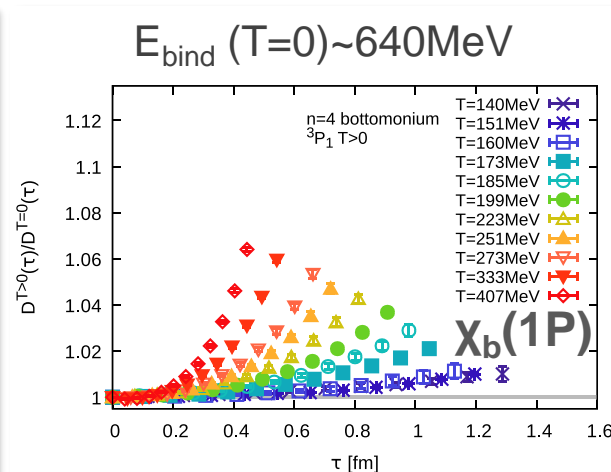
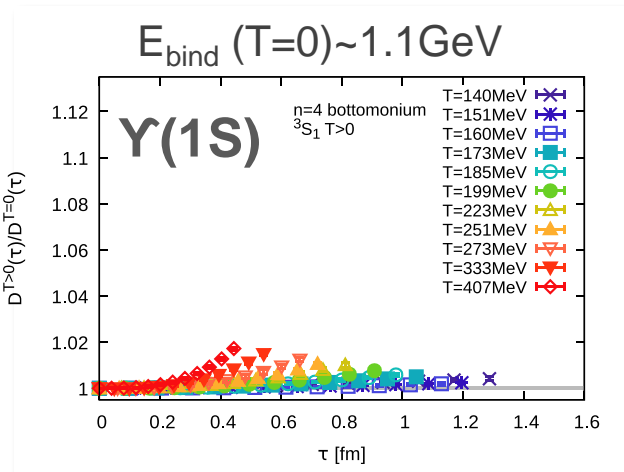
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Max 35MeV deviation. (HFS: NRQCD $O(v^6)$ and $O(\alpha_S v^4)$)

Reasonable agreement but no competition with high-prec. T=0 NRQCD

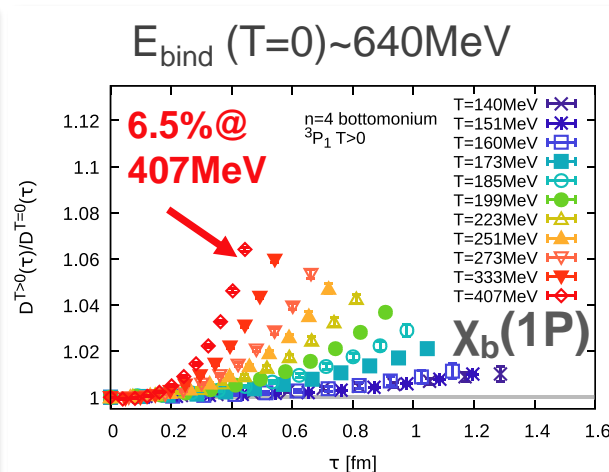
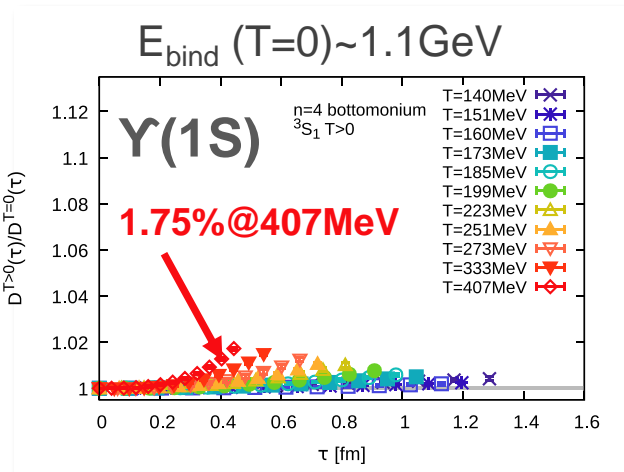
Correlator ratios



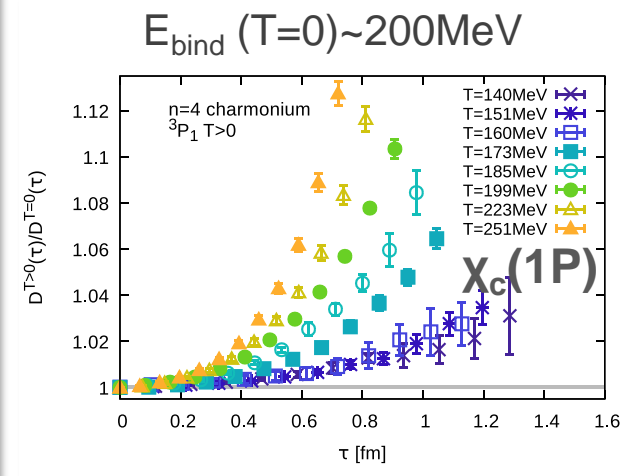
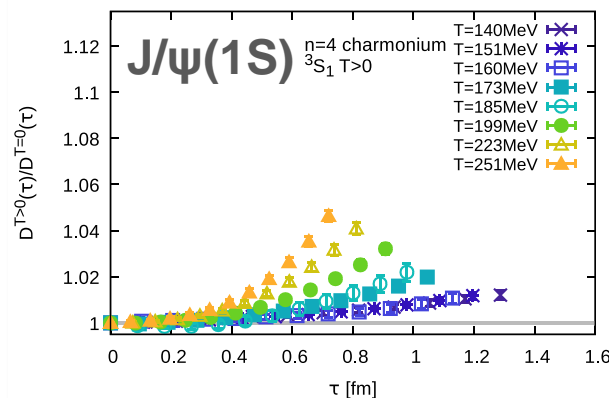
- Significant upward bent in the QGP phase
- Already in hadronic phase deviations from unity

■ In-medium modification hierarchically ordered with vacuum binding energy

Correlator ratios

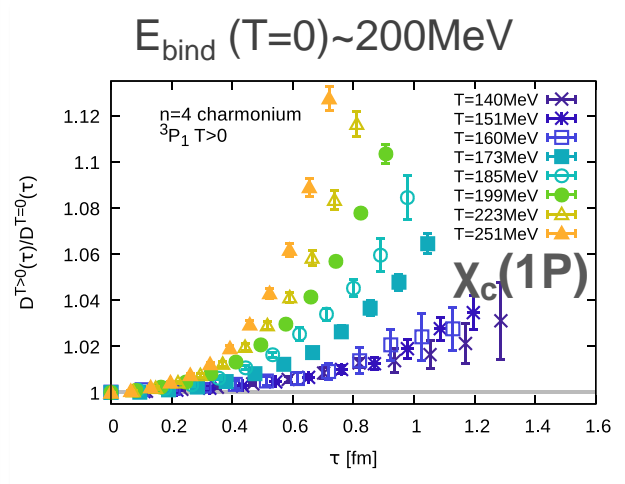
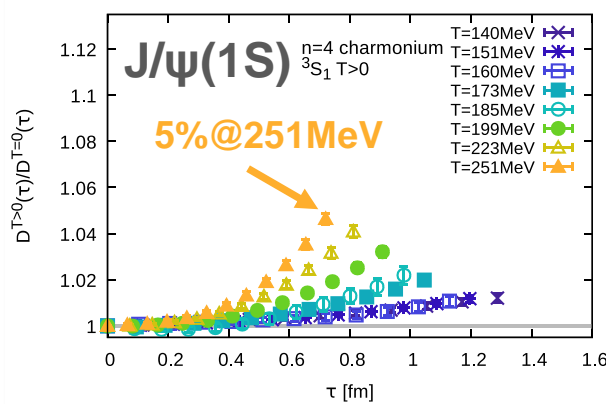
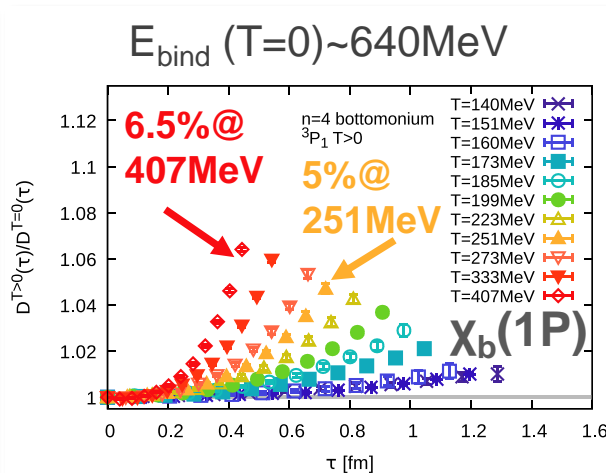
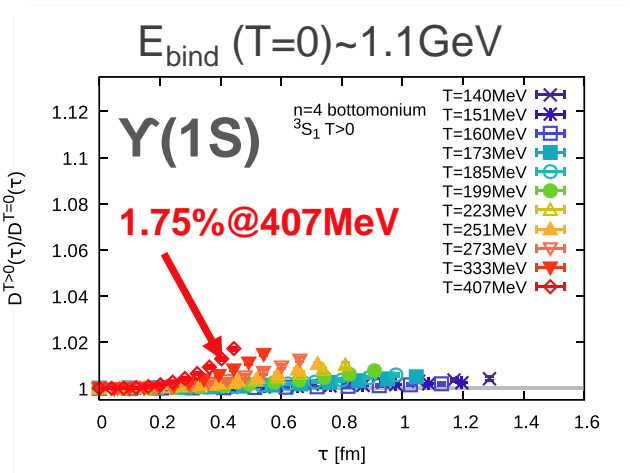


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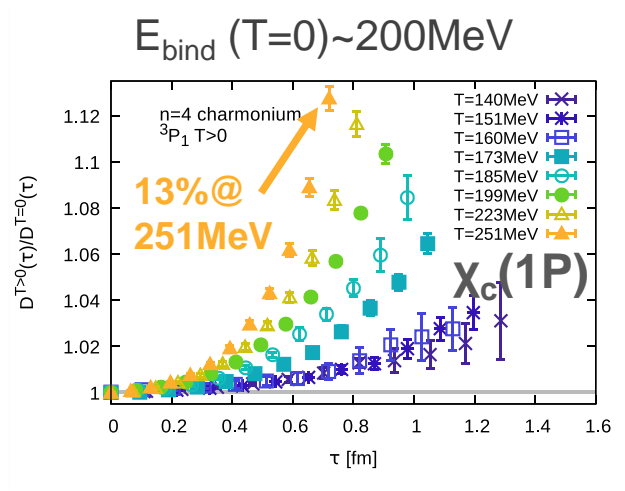
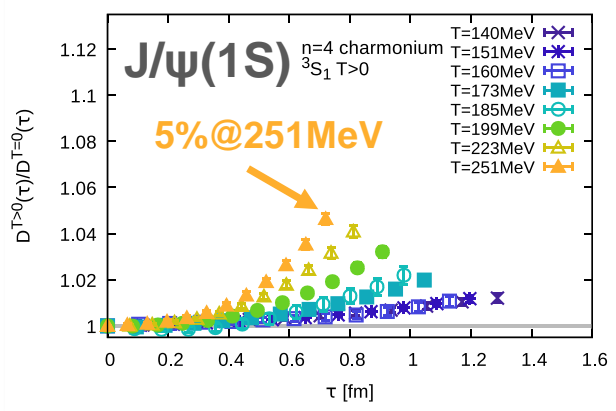
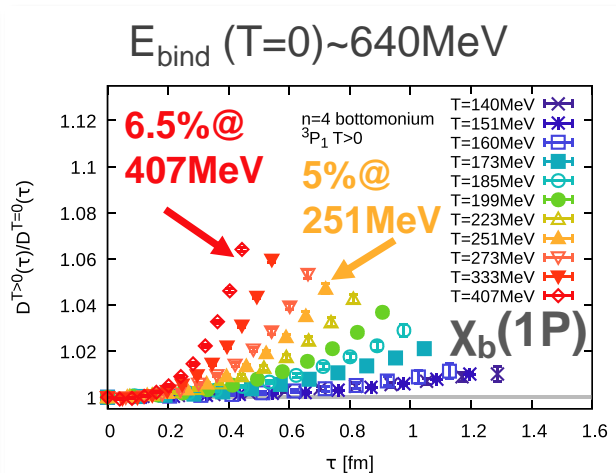
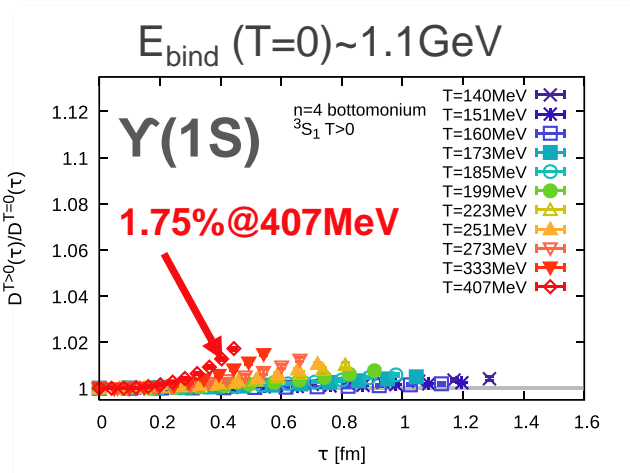
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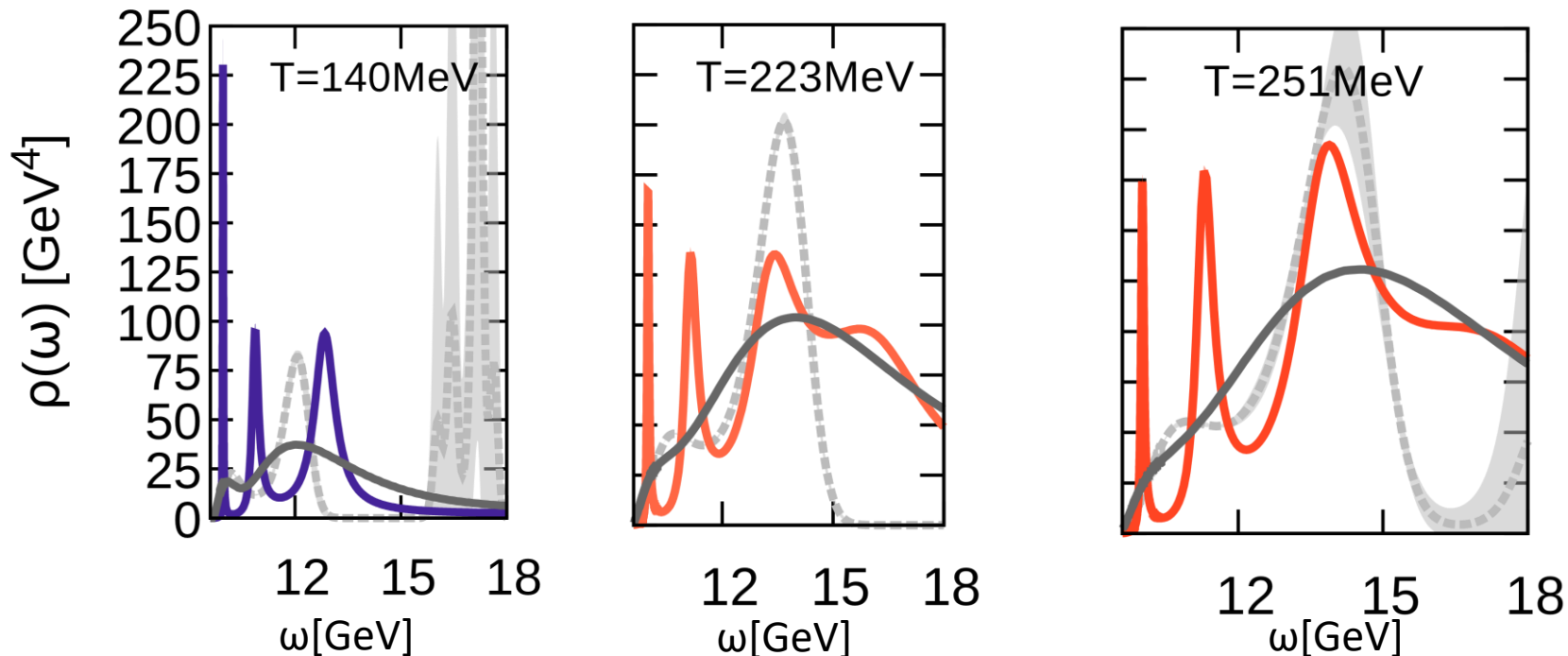
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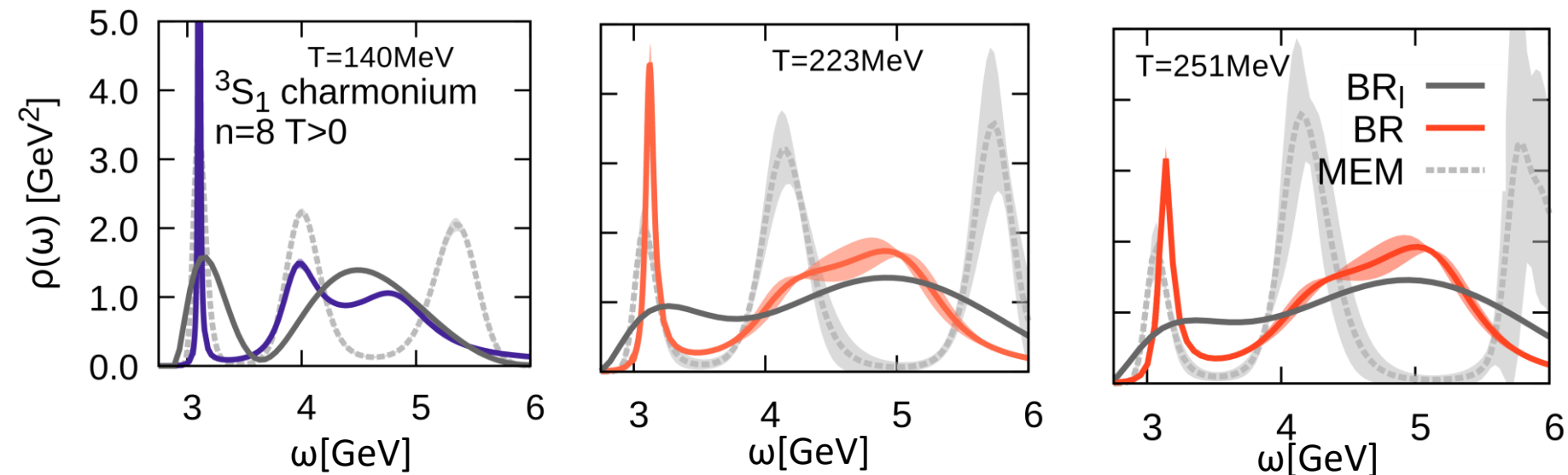


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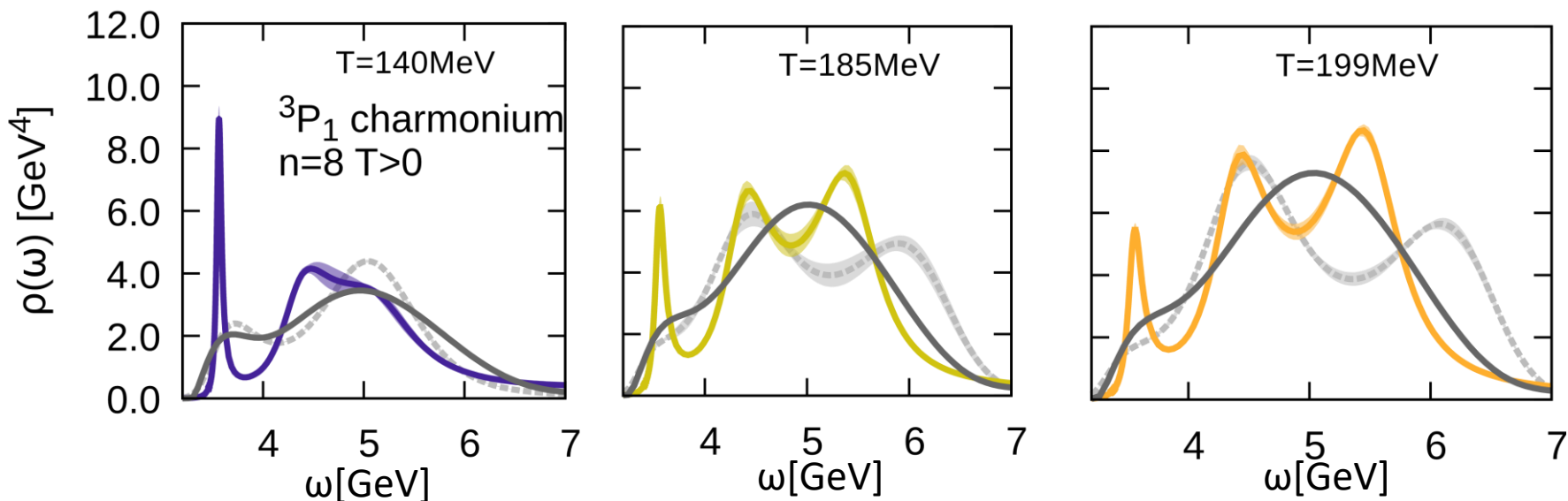


- Three methods: BR (colored), smooth BR (gray solid) & MEM (gray dashed)
 - At $T=199\text{MeV}$: all methods show remnant structure (threshold enhancement?)
 - For $199 < T < 233\text{MeV}$: only original BR shows peak (amplitude higher than next structure)
 - For $T > 233\text{MeV}$: lowest peak in original BR smaller than next, most likely ringing

Charmonium S-wave melting at $T > 0$ 

Three methods: BR (colored), smooth BR (gray solid) & MEM (gray dashed)

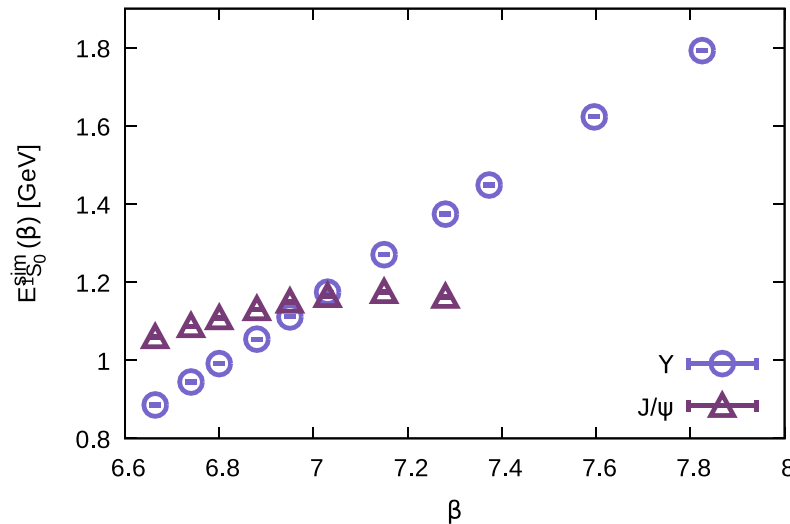
MEM and BR find peak at $T=251$ MeV, smooth BR washed out at $T > 200$ MeV

Charmonium P-wave melting at $T > 0$ 

- Three methods: BR (colored), smooth BR (gray solid) & MEM (gray dashed)
 - At $T < 185 \text{ MeV}$: all methods show remnant structure (threshold enhancement?)
 - For $T = 185 \text{ MeV}$: only original BR shows peak (amplitude higher than next structure)
 - For $T > 185 \text{ MeV}$: lowest peak in original BR smaller than next, most likely ringing

Energy calibration

- In NRQCD energy needs extra calibration (shift by $2m_q$):

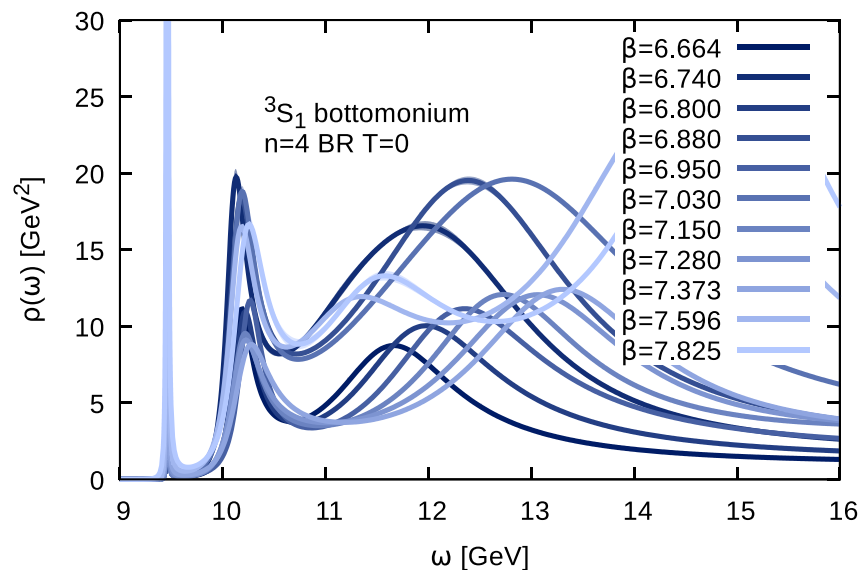


$$M_{s\chi_J}^{\text{exp}} = E_{s\chi_J}^{\text{sim}} + 2(Z_{M_q} M_q - E_0)$$



Use PDG value for
S-wave ground state

T=0 spectral reconstructions



Reconstruction parameters:

$N_\omega=2000$ frequency bins, $\omega a=[-5,20]$

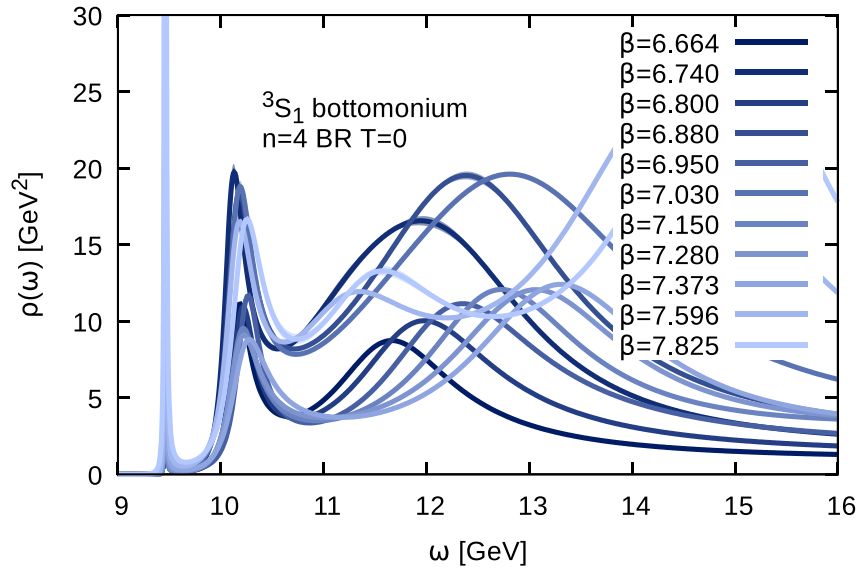
$N_\omega=600$ bin high res. interval around GS peak

$m(\omega)=\text{const.}$ statistical errors from 10-bin jackknife

systematic errors from variation of default model

varying reconstructed peak heights since N_τ different

T=0 spectral reconstructions



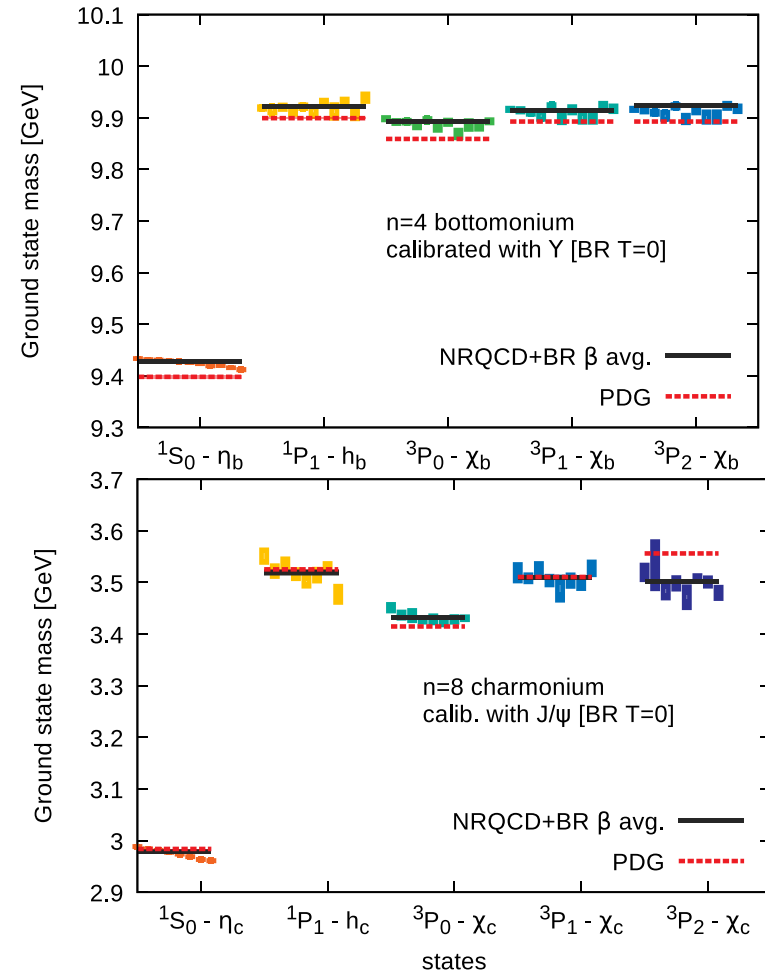
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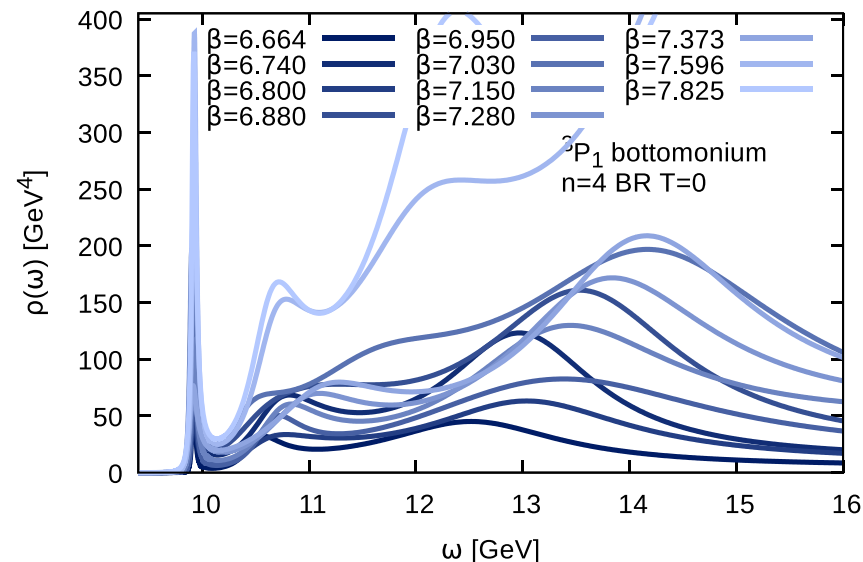
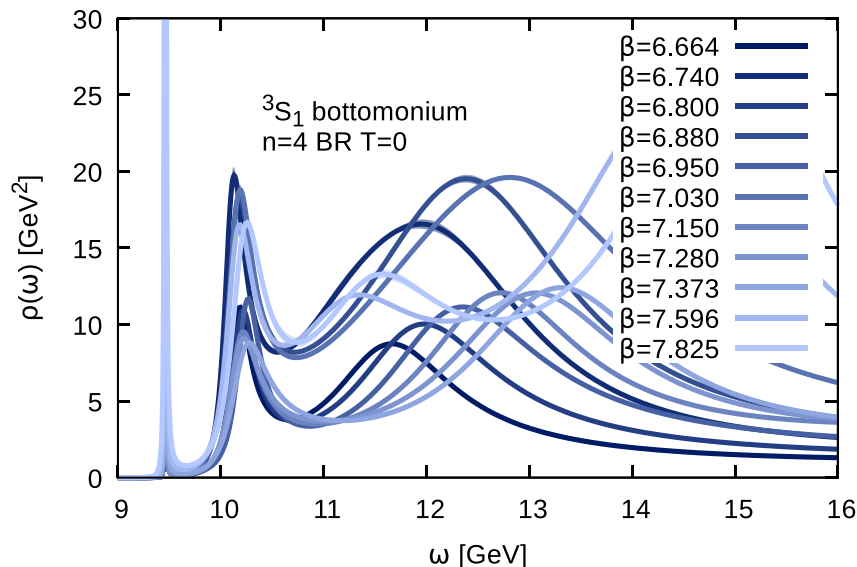
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systematic errors from variation of default model

varying reconstructed peak heights since N_τ different



GS peak position agree among effective mass fit and BR reconstruction

T=0 spectral reconstructions



Reconstruction parameters:

$N_\omega=2000$ frequency bins, $\omega_a=[-5,20]$

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systematic errors from variation of default model

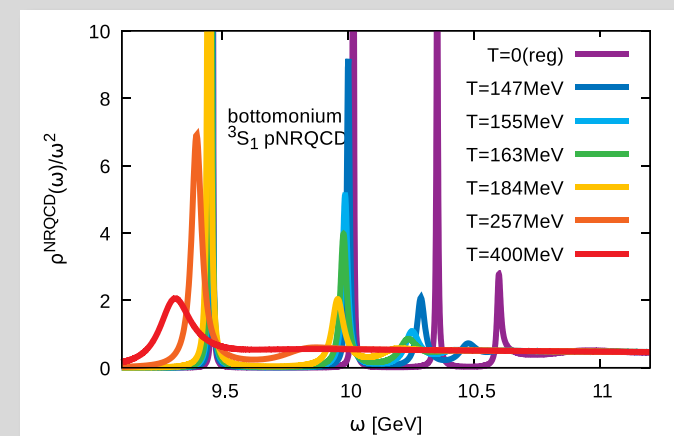
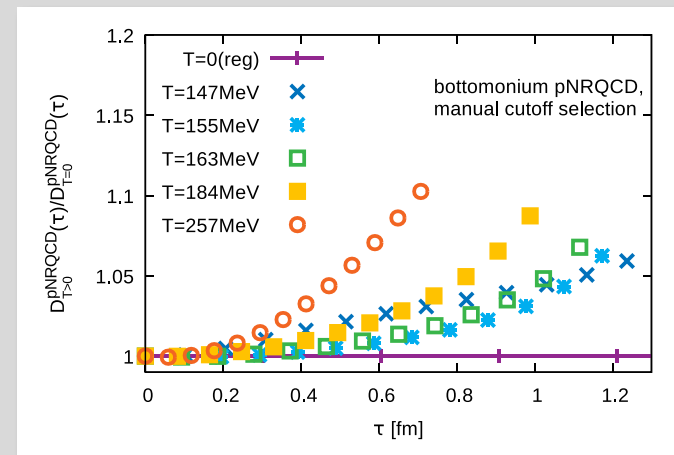
- Combined Euclidean and imaginary frequency data: less ringing at large ω
- GS peak position agree among effective mass fit and BR reconstruction

Interpreting the ratios

Behavior in ratios qualitatively reproduced by potential based computation

- Strong upward bend: ground state moves to smaller mass

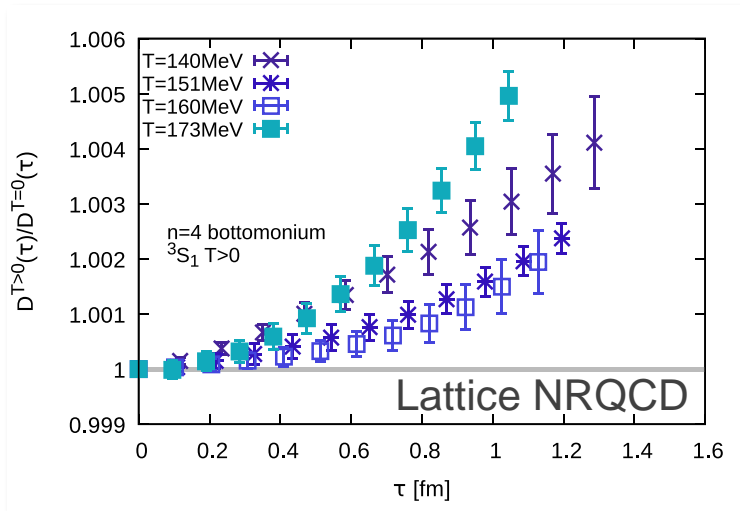
Lattice QCD potential based computation



Interpreting the ratios

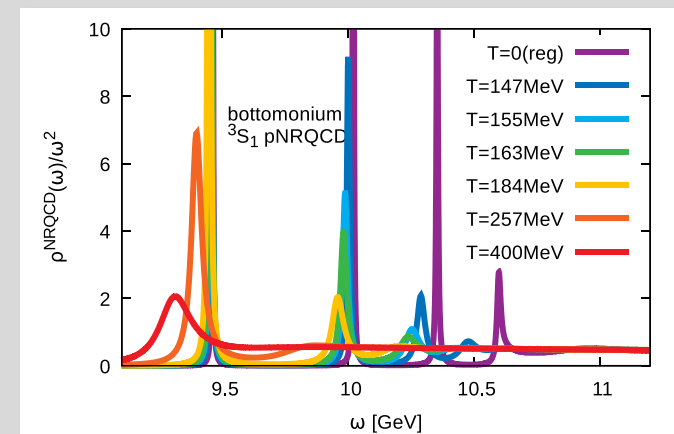
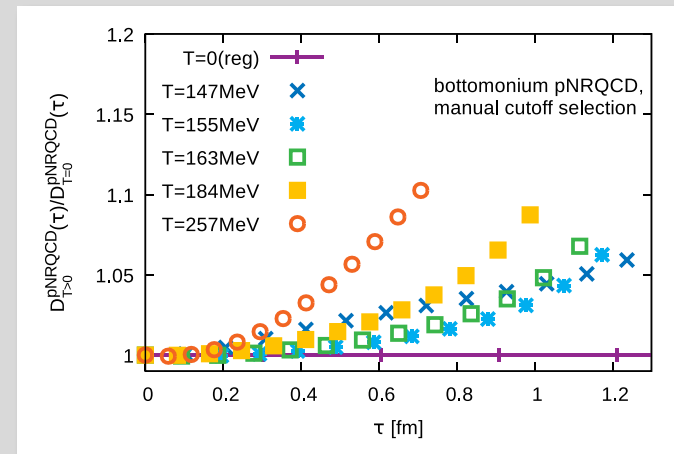
- Behavior in ratios qualitatively reproduced by potential based computation

- Strong upward bend: ground state moves to smaller mass



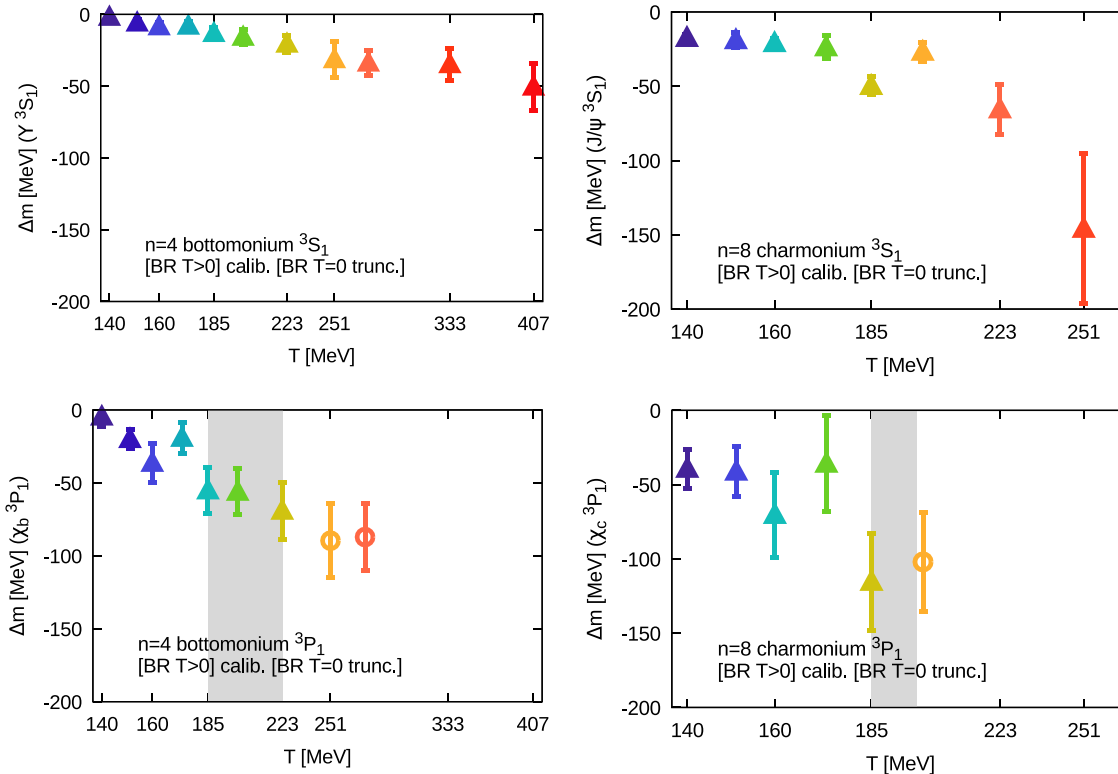
- Non-monotonicity only in the Bottomonium S-wave: destabilization of excited states

Lattice QCD potential based computation

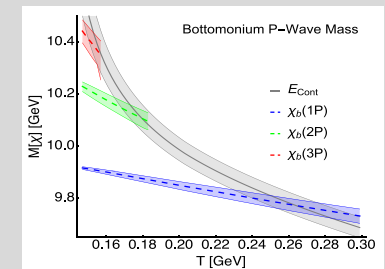
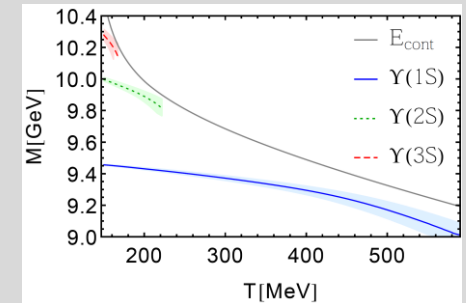


In-medium mass shifts II

Our direct lattice NRQCD result for $T>0$ mass shifts



Lattice QCD potential based computation



- Negative mass shifts in qualitative agreement with potential based computation (i.e. with a non-perturbative implementation of the EFT pNRQCD)