



Nuclear Science
Computing Center at CCNU

Machine learning Hadron Spectral Functions in Lattice QCD

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Based on arXiv:2110.13521 in collaboration with
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Partner institute

Nuclear **S**cience **C**omputing **C**enter

at **C**entral China Normal University(CCNU)



N: Nuclear **S**: Science **C**³: Color 3 -> QCD



Built in September 2018

Theoretical Peak (Rpeak):

2.7 PFlop/s (peta flops per second)

GPUs: 306 Nvidia V100 + 30 A100

Word Rand	2018	2019	2020
The logo for the TOP 500 list, featuring the text 'TOP 500' in a stylized font with a yellow and orange gradient, and 'The List.' below it.	466	389	432
The logo for THE GREEN 500, featuring the text 'THE GREEN 500' in a stylized font with a green and grey gradient, and a small green leaf icon.	268	13	17

Cooperation with ELTE: Machine learning Hadron Spectral Functions in Lattice QCD

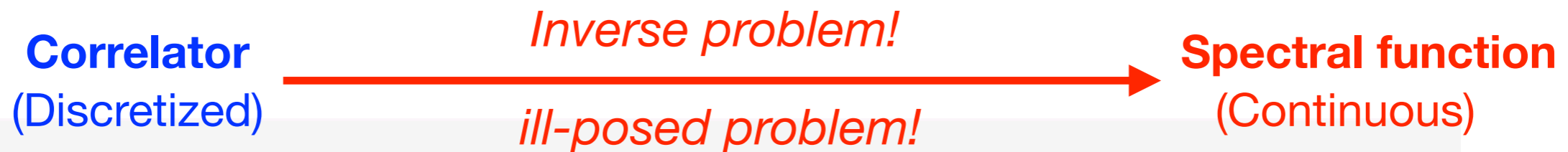
An ill-posed problem in hadron spectral function

Hadron spectral functions: Carry all information about hadrons

1. Quarkonia dissociation temperature T. Matsui & H. Satz, PLB 178, 416 (1986)

2. Heavy Quark diffusion coefficient P. Petreczky & D. Teaney, PRD 73,1649 (2006)

Reconstruction



$$\boxed{\mathcal{O}(10)} \quad G(\tau, T) = \sum_{x,y,z} \langle J_H(0, \vec{0}) J^+(\tau, \vec{x}) \rangle_T = \int_0^\infty \frac{d\omega}{2\pi} K(\tau, \omega, T) \boxed{\mathcal{O}(1000)} \rho(\omega)$$

$$K(\omega, \tau, T) = \frac{\cosh(\omega(\tau - \frac{1}{2T}))}{\sinh(\frac{\omega}{2T})}$$

Common methods:

1. Maximum Entropy Method (MEM) Asakawa, Hatsuda & Nakahara, (2001)

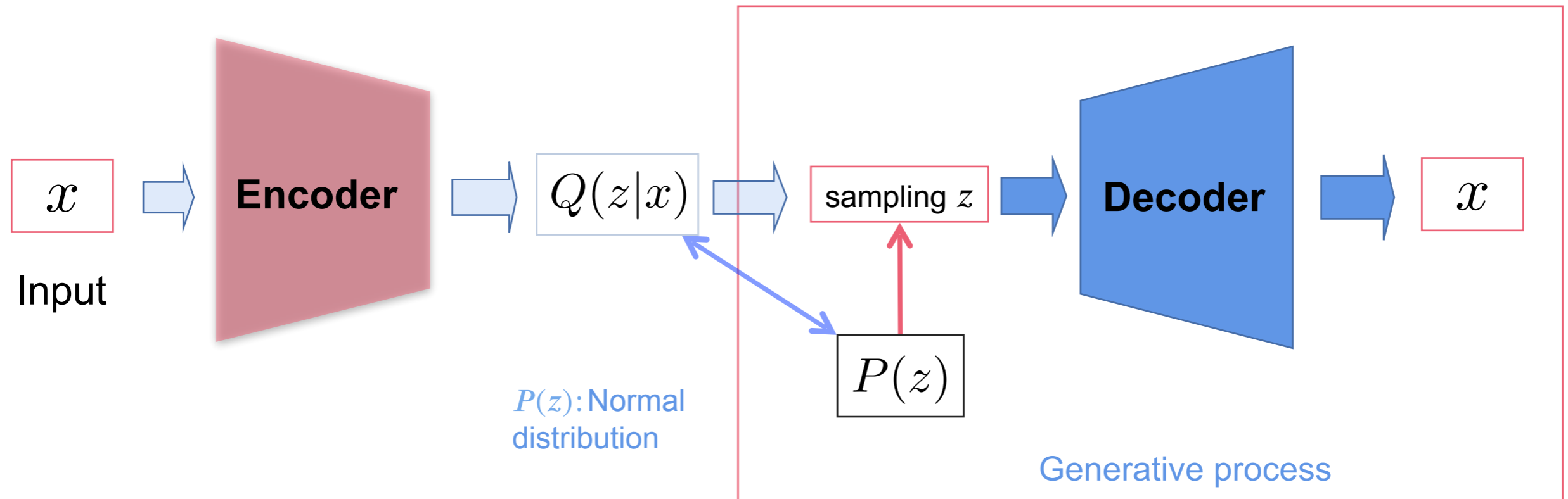
2. Backus Gilbert method G. Backus et al, Geophysical Journal International 16, 169(1968)

3. New Bayesian Method (improved MEM) Y. Burnier et al, PRL 111,182003 (2013)

4. Stochastic Approaches H.-T. Ding et al., PRD 97, 094503 (2018)

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Variational AutoEncoder (VAE) C.Doersch, arXiv:1606.05908



Natural tool to tackle the inverse problem.

- Our Goal:**
- 1. Find certain constraints on latent space Z .**
 - 2. Design a neural network that can learn to balance the prior & likelihood.**
 - 3. Train the neural network using a general input**

A newly structure of VAE

To reconstruct ρ from $G \longrightarrow P(\rho|G)$ (Conditional probability)

$$\log P(\rho | G) = \log \left[\int P(\rho | z, G) P(z | G) dz \right]$$

=

$$\log \left[E_{Q(z|\rho_{gt}, G_{gt})} \left(P(\rho | z, G) \frac{P(z | G)}{Q(z | \rho_{gt}, G_{gt})} \right) \right]$$

$$E_{Q(z|\rho_{gt}, G_{gt})}(f(z)) = \int dz f(z) Q(z | \rho_{gt}, G_{gt})$$

Jensen's inequality & the concave feature of the logarithm function

$$\geq E_{Q(z|\rho_{gt}, G_{gt})} \left(\log P(\rho | z, G) \frac{P(z | G)}{Q(z | \rho_{gt}, G_{gt})} \right)$$

• Define loss function = - Evidence lower bound

$$\mathcal{L} = - E_{Q(z|\rho_{gt}, G_{gt})} \left(\log P(\rho | z, G) \frac{P(z | G)}{Q(z | \rho_{gt}, G_{gt})} \right)$$

$$\int dz Q(z | \rho_{gt}, G_{gt}) \log \left(\frac{Q(z | \rho_{gt}, G_{gt})}{P(z | G)} \right)$$

KL divergence gives the difference between 2 probabilities expected to denoise

$$= - E_{Q(z|\rho_{gt}, G_{gt})} (P(\rho | z, G)) + KL(Q(z | \rho_{gt}, G_{gt}) || P(z | G))$$

$$P(\rho | z, G) = P(\rho | G) P(G | \rho, z) / P(G | z)$$

Prior information Likelihood Evidence

SVAE

$$\mathcal{L} = - E_{Q(z|\rho_{gt}, G_{gt})} \left(\frac{P(\rho|G)P(G|\rho, z)}{P(G|z)} \right) + KL(Q(z|\rho_{gt}, G_{gt}) || P(z|G))$$

Prior information: $P(\rho|G) = \frac{1}{Z_s} e^S, \quad S = \int d\omega \rho_{gt} - \rho(z) - \rho(z) \log \frac{\rho(z)}{\rho_{gt}}.$

Shannon-Jaynes entropy term: ground truth

ρ_{gt} : ground truth value of the spectral function, best prior information of ρ !

Likelihood: $P(G|\rho, z) = \frac{1}{Z_L} e^{-L}, \quad L = L_j = \sum_j \frac{(\hat{G}_j[\rho(z)] - G_j)^2}{\alpha^2(z)G_j^2}.$

From Maximum Entropy Method (MEM)

G: correlator data
 \hat{G} : computed from $\rho(z)$

$\alpha(z)$: controls the relative weight of the entropy (having ρ close to the prior)
and the likelihood (having $\rho(z)$ close to the data G)

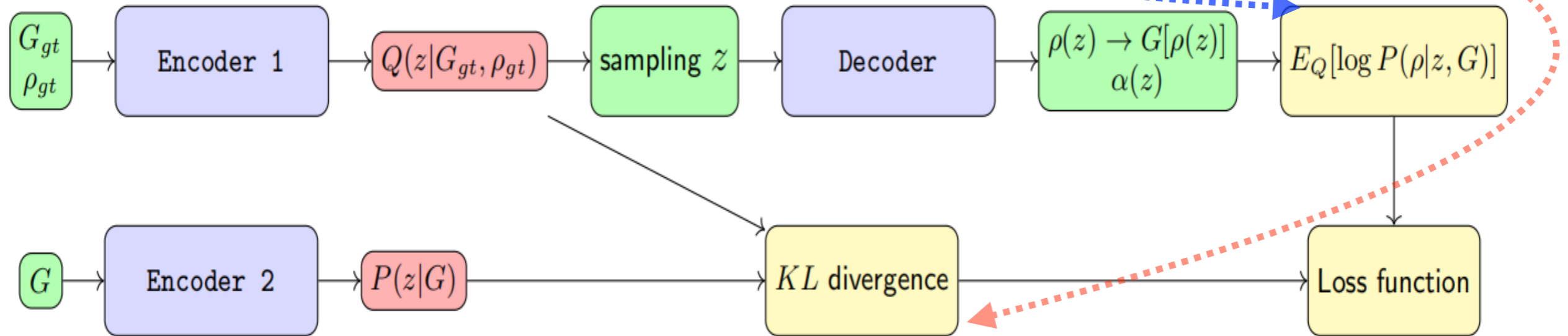
Evidence: $P(G|z) = \int \mathcal{D}\rho(z) P(\rho|G) P(G|\rho, z) = \int \mathcal{D}\rho(z) \frac{1}{Z_s Z_L} e^{-L+s}$

Topology of SVAE

$$\mathcal{L} = -E_{Q(z|\rho_{gt}, G_{gt})} \left(\frac{P(\rho|G)P(G|\rho, z)}{P(G|z)} \right) + KL(Q(z|\rho_{gt}, G_{gt}) || P(z|G))$$

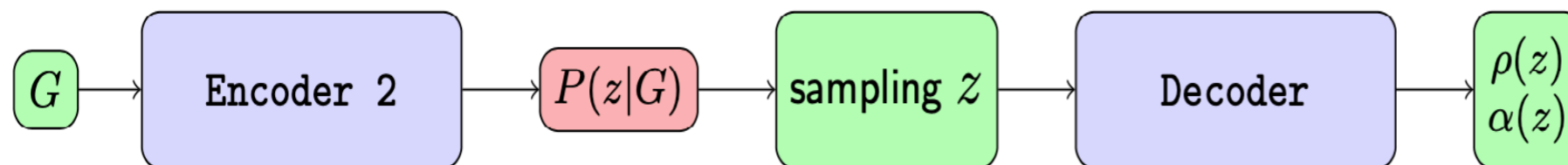
Epoch = 5 million

Training:



1. feed ground truth value G_{gt} and ρ_{gt} into Encoder 1
2. feed G generated stochastically to Encoder2;
Noisy G is sampled from a Gauss distribution $N(G_{gt}, \sigma)$ with $\sigma = b \times G_{gt}$ and $b = \sigma_{latt}/G_{latt}$
3. Perform the feeding in steps 1 and 2 simultaneously
4. For each repeat steps 1, 2 & 3.

Reconstruction:



A general spectral function used for the training

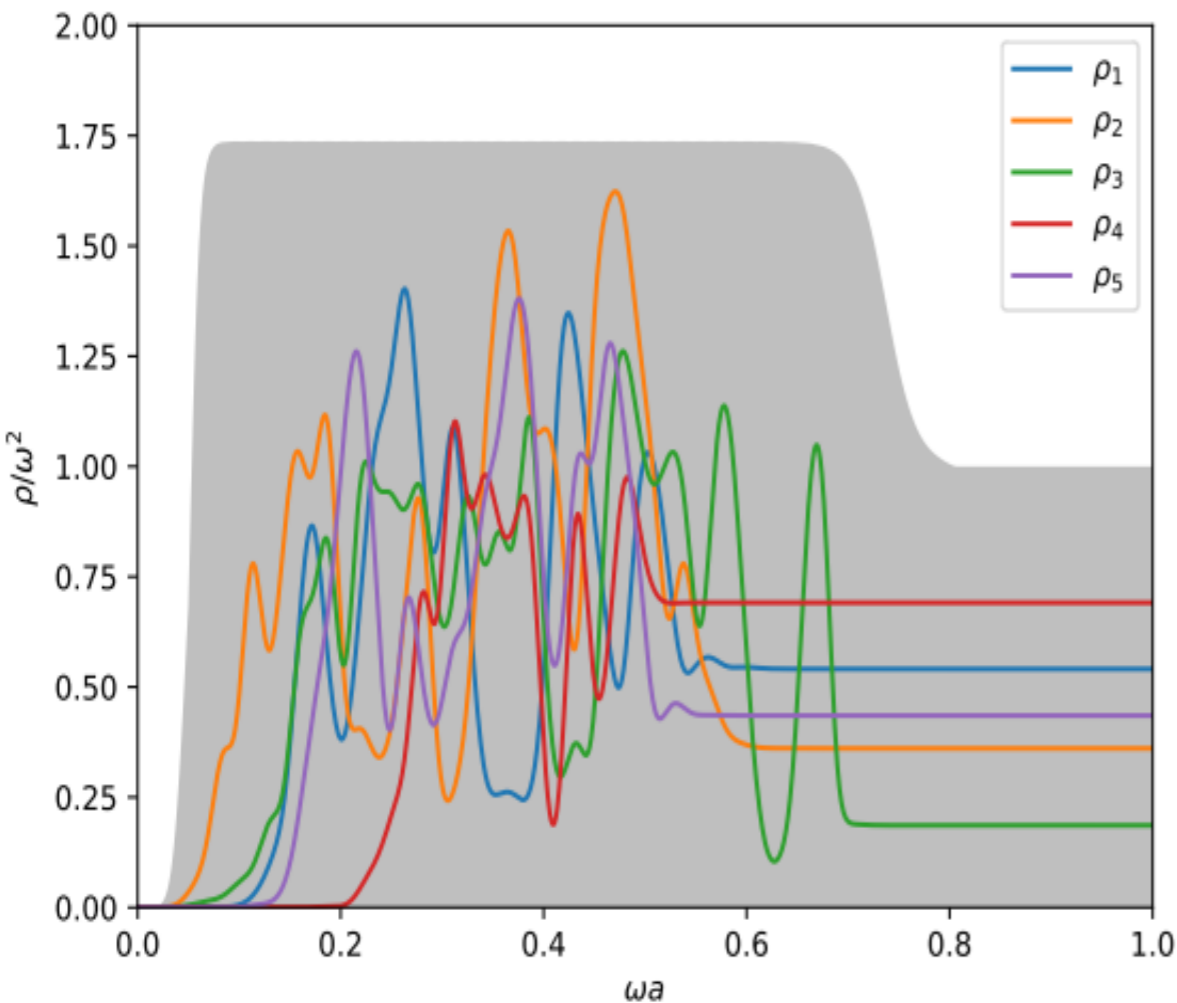
$$\frac{\rho_{train}}{\omega^2} = \hat{\theta}(\omega, \delta_1, \zeta_1) \left(\underbrace{\sum_{i=1}^{\hat{N}_g} C_i e^{-\left(\frac{\omega - M_i}{\gamma}\right)^2}}_{\text{Gaussian peaks}} \left(1 - \hat{\theta}(\omega, \delta_2, \zeta_2)\right) + \underbrace{C_0 \hat{\theta}(\omega, \delta_2, \zeta_2)}_{\text{continuum part}} \right)$$

M_i : peak location with fixed interval γ : fixed peak width

$C_0 \in [0, 1]$

$\hat{N}_g = 50$, number of Gauss peaks

Step functions: $\hat{\theta}(\omega, \delta_i, \zeta_i) = \frac{1}{1 + \exp\left(-\frac{\omega - \delta_i}{\zeta_i}\right)}$



Training samples

Parameters	interval	Parameters	interval
M_i	[0.05, 0.8]	$\zeta_2 (\sim [0.1, 0.2] m_c)$	[0.005, 0.02]
C_i	[0, 1]	$\delta_1 (\sim [1, 3] m_c)$	[0.05, 0.3]
$\zeta_1 (\sim [0.1, 0.2] m_c)$	[0.005, 0.02]	$\delta_2 (\sim 8 m_c)$	$[\delta_1 + 0.1, \delta_1 + 0.6]$

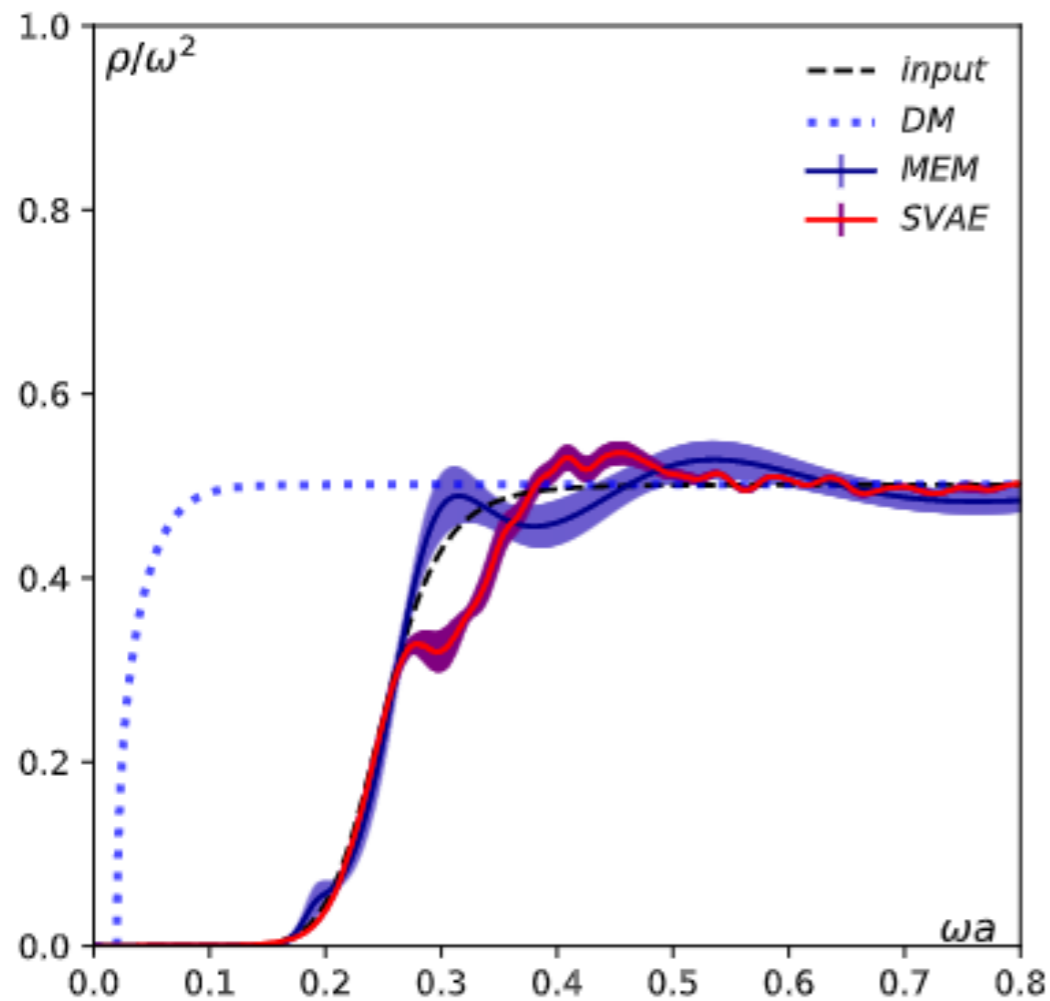
The parameters are set according to the theoretically range of physics.

H. T. Ding et al, Phys. Rev. D 86, 014509 (2012)

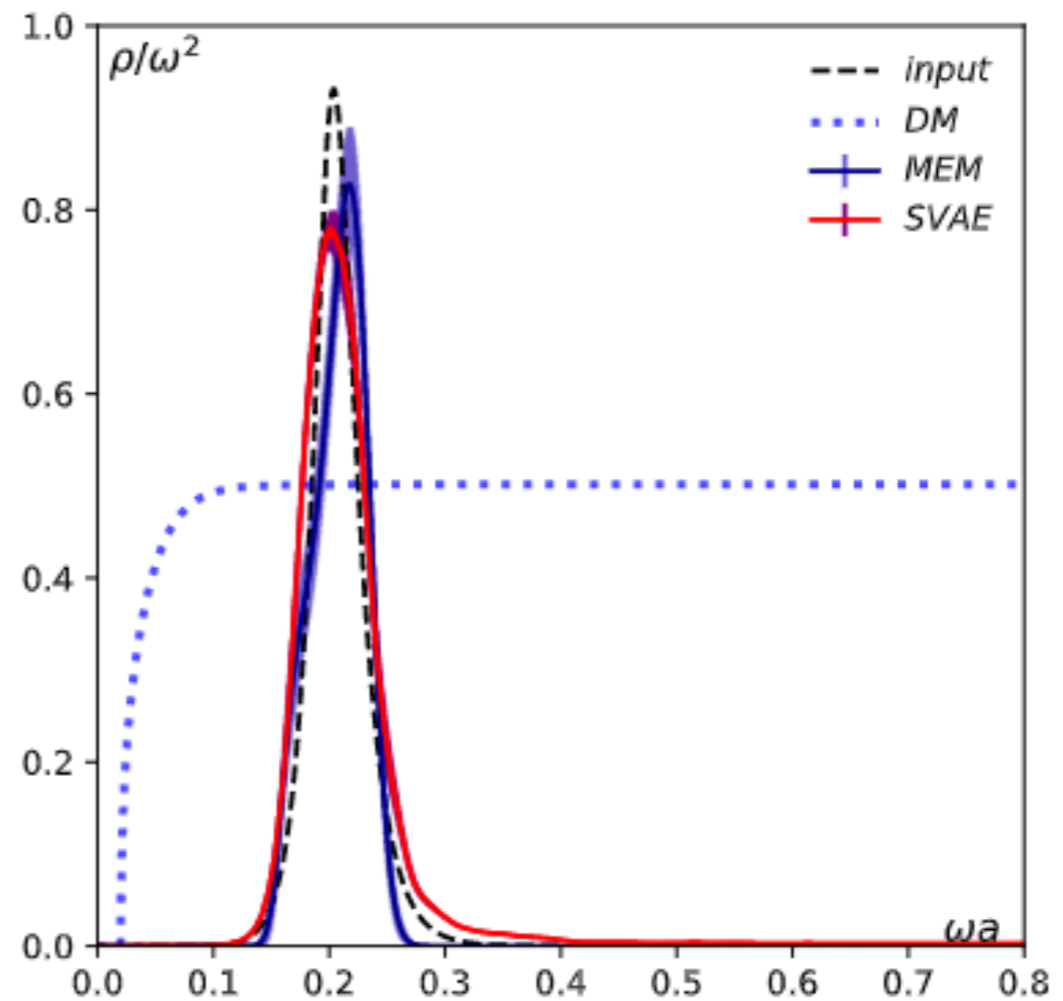
Mock data test I: simplest cases

Temporal extent $N_\tau = 96$

MEM results depend on the chosen of default model (DM)



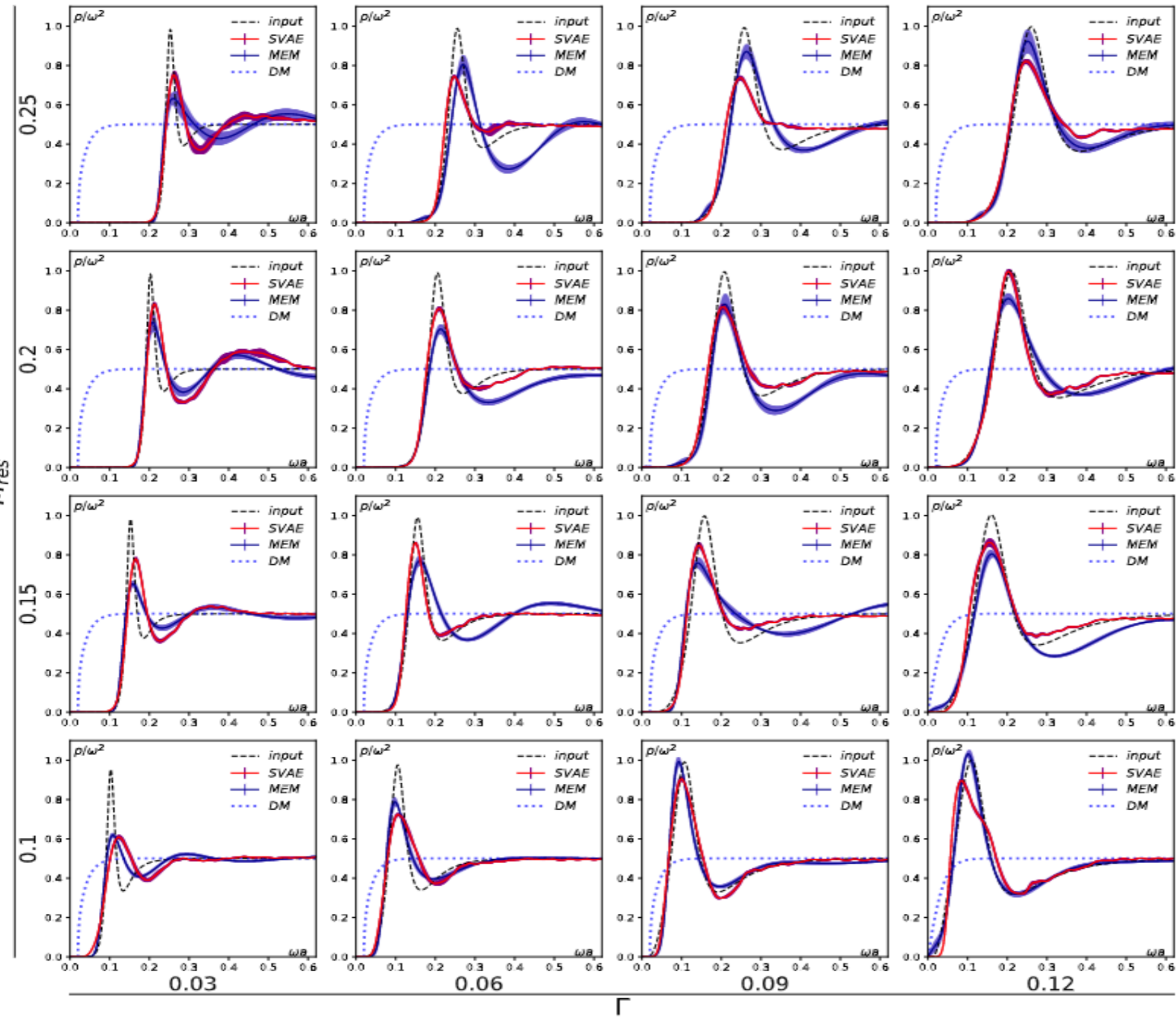
Only a **continuum** part



Only a **resonance** peak

Both output spectral functions from the **SVAE** and **MEM** can more or less reproduce the input spectral functions

Mock data test II: A resonance peak + continuum part



$N_\tau = 96$

Charm quark

Peak location

$M_{res} = 0.1, 0.15, 0.2, 0.25$

Peak width

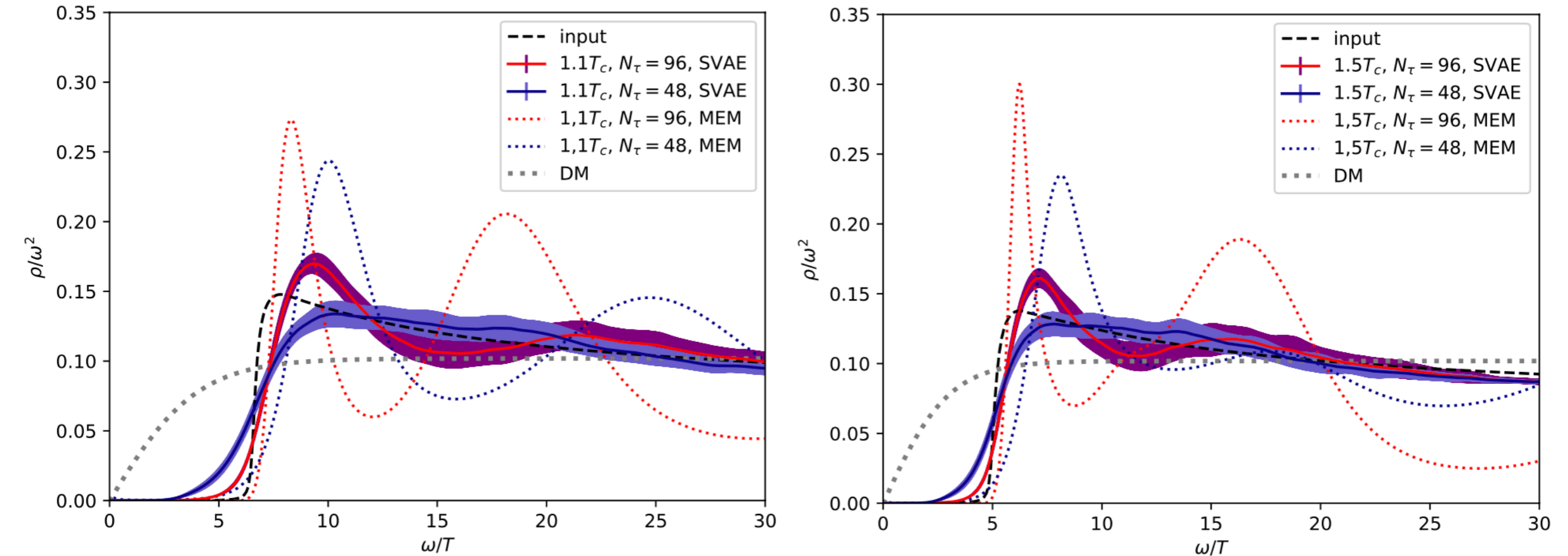
$\Gamma = 0.03, 0.06, 0.09, 0.12$

Reconstruction quantity depends more on Γ rather than M_{res}

Mock data test III: Non-relativistic QCD

Input ρ obtained from the Non-relativistic QCD (NRQCD)

Y. Burnier et al, JHEP 2017 (11), 206

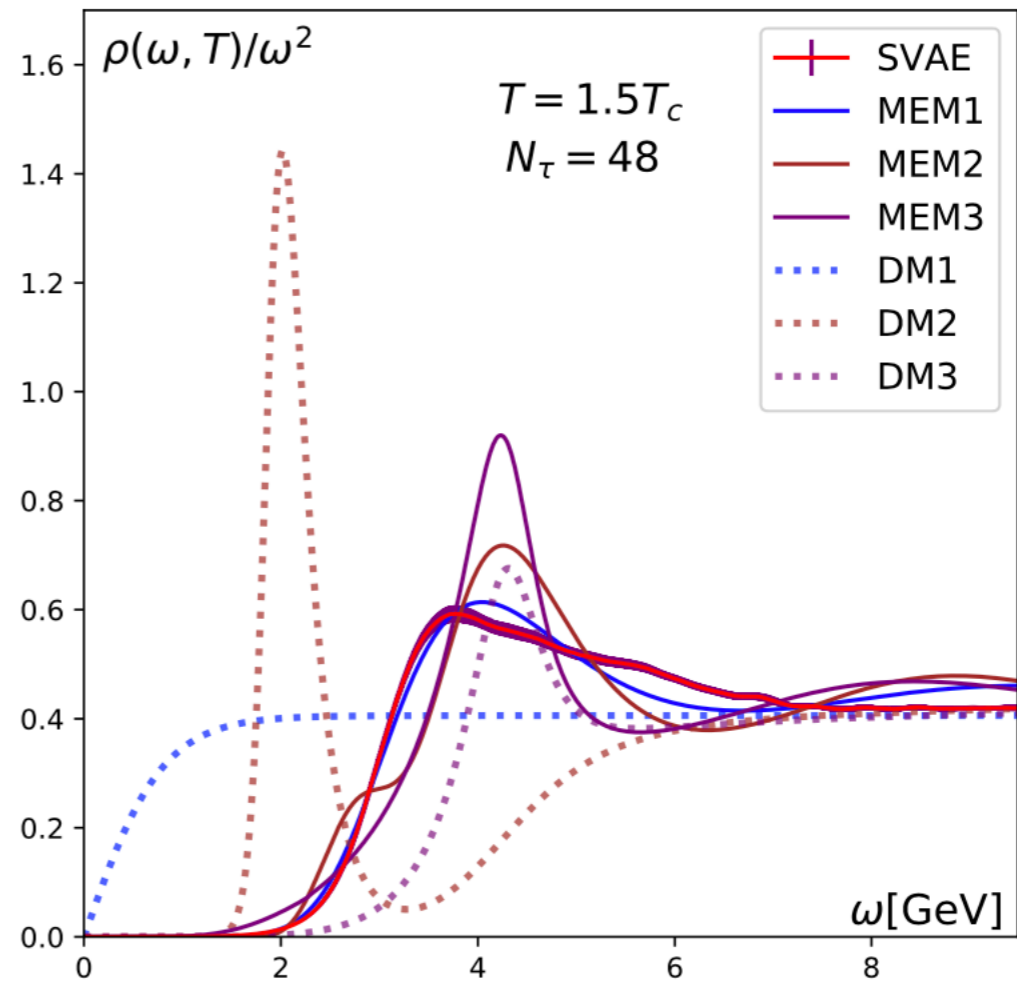
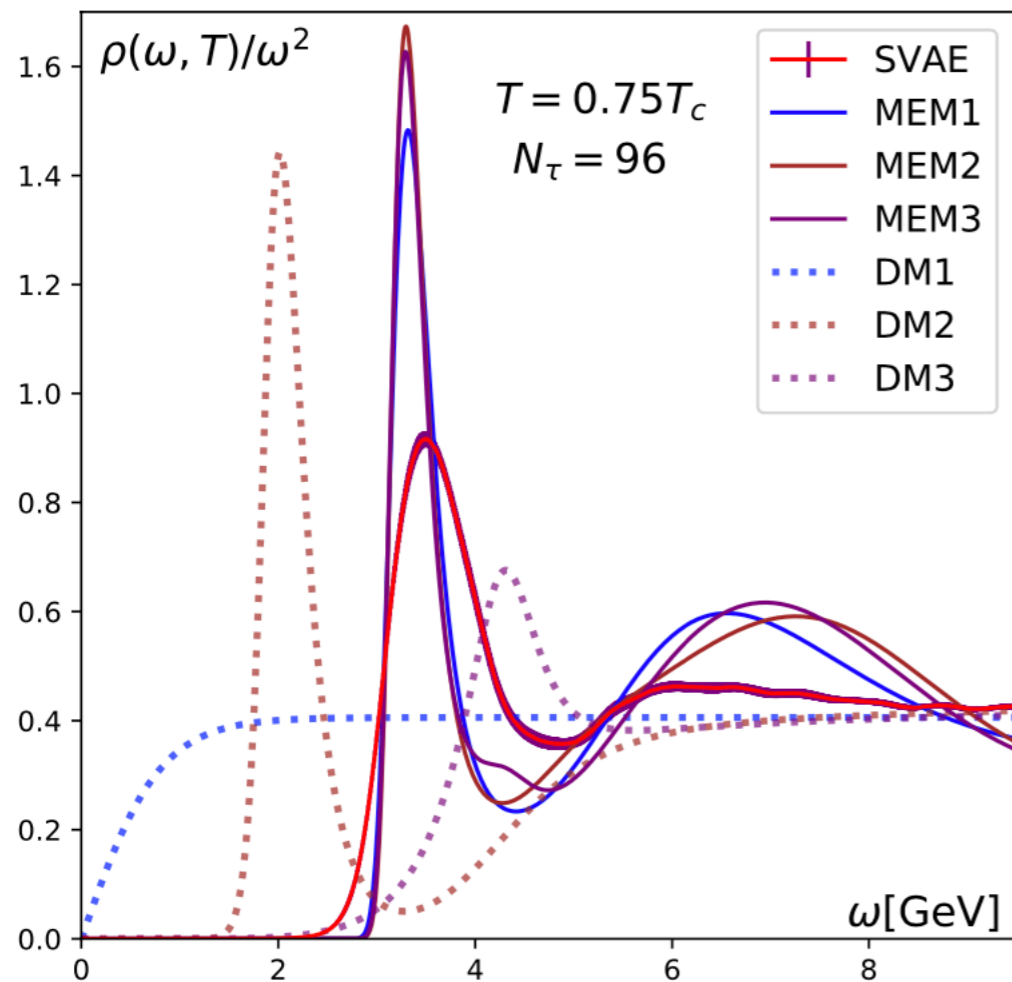


Although the **SVAE** results are closer to the mock data, both the **SVAE** and **MEM** cannot reproduce the input NRQCD spectral function in a satisfactory way.

Application to Charmonium correlator in the pseudo-scalar(η_c) channel

Correlators computed on the finest lattices $128^3 \times 96(0.75T_c)$ and $128^3 \times 48(1.5T_c)$ with a fixed scale approach.

H. T. Ding et al, Phys. Rev. D 86, 014509 (2012)



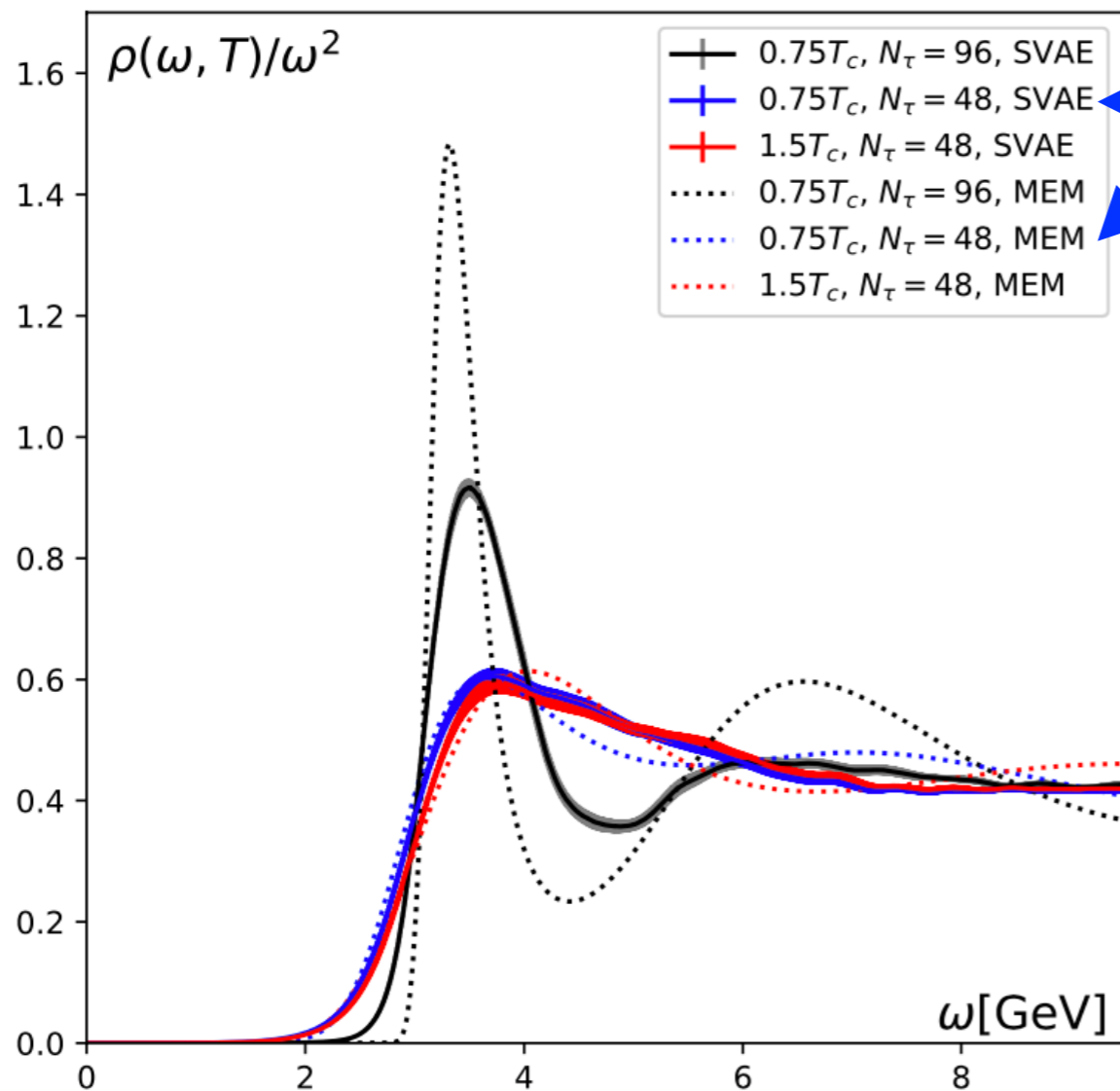
- Peak locations reconstructed from these two methods are more reliable compared to the peak height

- Based on the results from both methods it seems that the resonance peak for η_c is substantially modified at $1.5T_c$

Application to Charmonium correlator in the pseudo-scalar(η_c) channel

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Reconstruct correlator with $N_\tau = 96$ to that with $N_\tau = 48$ of ρ fixed at $0.75 T_c$

$$G_{rec}(\tau, T; T') = \int d\omega K(\tau, T; T') \rho(\omega, T')$$

$$= \sum_{\tau'=\tau}^{N'_\tau - N_\tau + \tau} G(\tau', T')$$

$$T = 1.5T_c, T' = 0.75T_c, N_\tau = 48, N'_\tau = 96$$

- $N_\tau = 48$: SVAE is consistent with MEM at both $0.75 T_c$ and $1.5T_c$.
- Output $\rho(\omega)$ larger depends on N_τ .

Summary & Outlook

- We propose a novel neural network, SVAE, which can be trained to obtain the most probable image of the spectral function
- The loss function of SVAE includes an entropy and a likelihood term which are balanced by a weight $\alpha(z)$
- For training: A general ρ is used with corresponding correlator having the error of correlators mimic to LQCD
- Mock tests shows that SVAE is comparable to MEM and even outperforms MEM in certain cases
- For the application to lattice QCD data of charmonium correlator in the pseudo-scalar channel, SVAE is consistent with MEM results.
- Output $\rho(\omega)$ larger depends on N_τ

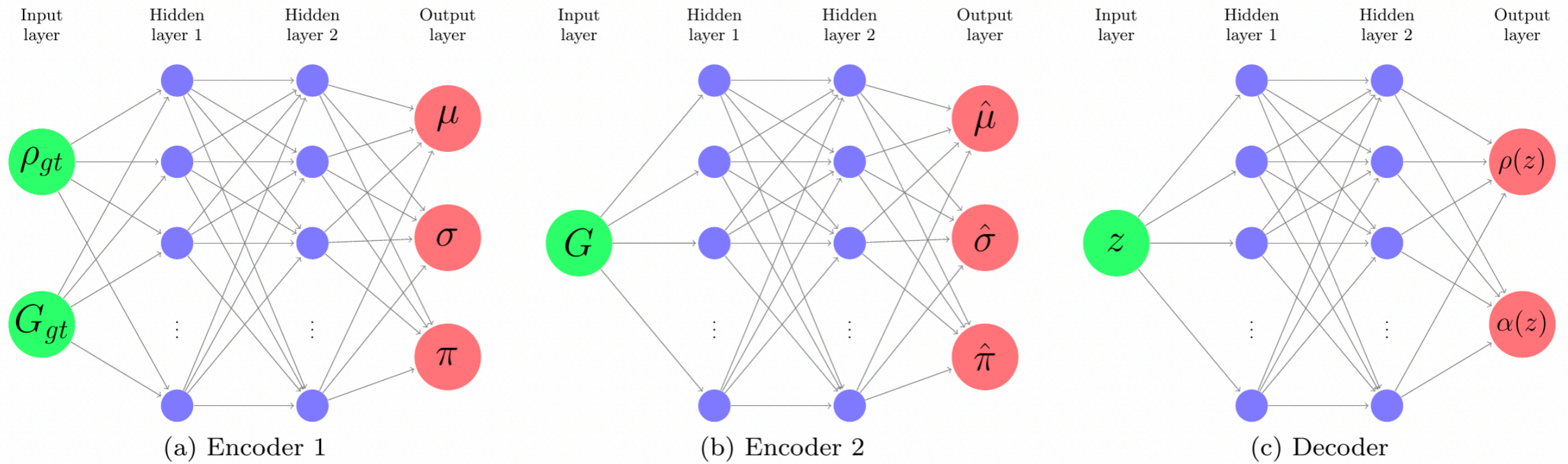
► Trial with a different kernel $K = \omega^2(\omega^2 + p^2)$ or $e^{-\tau\omega}$

$$G(\tau, T) = \int_0^\infty \frac{d\omega}{2\pi} K(\omega, \tau, T) \rho(\omega, T) \quad \text{Current: } K(\omega, \tau, T) = \frac{\cosh(\omega(\tau - \frac{1}{2T}))}{\sinh(\frac{\omega}{2T})}$$

Thank you!

Back up

Networks

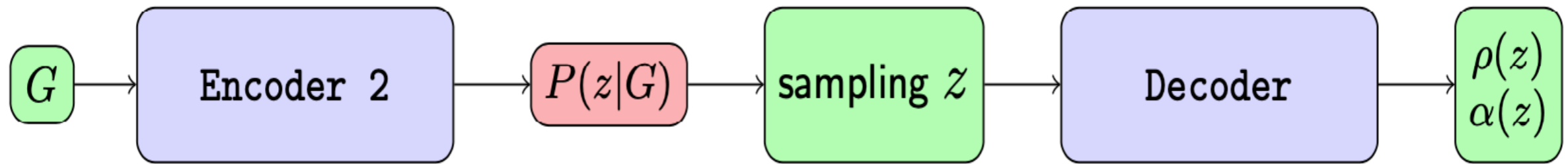


$$Q(z|\rho_{gt}, G_{gt}) = \sum_i^{N_g} \pi_i \prod_k^{N_z} \mathcal{N}(\mu_{i,k}, \sigma_{i,k}) \quad P(z|G) = \sum_i^{N_g} \hat{\pi}_i \prod_k^{N_z} \mathcal{N}(\hat{\mu}_{i,k}, \hat{\sigma}_{i,k}).$$

Q and P(z|G): parameterized based on the Gauss mixture model with \mathcal{N} the Gauss function, outputs from Encoder 1 and 2

$\rho(z), \alpha(z)$: outputs of Decoder

Topology of the sVAE for reconstruction



$$\begin{aligned} \tilde{\rho}_{\Theta} &= \frac{1}{N_c} \sum_{m=1}^{N_c} \int dz \rho(z) P(G_m | \rho, z) P(z | G_m) \\ &\rightarrow \frac{1}{N_c} \sum_{m=1}^{N_c} \sum_{n=1}^{N_s} \frac{\rho(z_n) P(G_m | \rho, z_n)}{\sum_{k=1}^{N_s} P(G_m | \rho, z_k)} \equiv \frac{1}{N_c} \sum_{m=1}^{N_c} \tilde{\rho}_{\Theta, m} \end{aligned}$$

N_s : Number of samples in Z space

N_c : Number of bootstrap samples in configurations space

Bootstrap method: 1. Firstly randomly choose an epoch Θ (uniformly)

2. At this certain epoch we sample N_c times of $\tilde{\rho}_{\Theta, m}$ uniformly: $\tilde{\rho}_i$

Final mean value and its uncertainty:

$$\bar{\rho} = \frac{1}{N_{btp}} \sum_{i=1}^{N_{btp}} \tilde{\rho}_i \quad \sigma_{\rho} = \sqrt{\frac{1}{N_{btp}} \sum_{i=1}^{N_{btp}} (\tilde{\rho}_i - \bar{\rho})^2}$$

N_{btp} : Number of bootstrap samples in model parameter space

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Correlators computed on the finest lattices $128^3 \times 96(0.75T_c)$ and $128^3 \times 48(1.5T_c)$ with a fixed scale approach.

H. T. Ding et al, Phys. Rev. D 86, 014509 (2012)

- At higher temperatures, the information of the spectral function is compressed into the correlation function with a short temporal extent

Reconstruct correlator with $N_\tau=96$ to that with $N_\tau=48$ with ρ fixed at $0.75 T_c$

$$G_{rec}(\tau, T; T') = \int d\omega K(\tau, T; T') \rho(\omega, T')$$

$$= \sum_{\tau'=\tau}^{N'_\tau - N_\tau + \tau} G(\tau', T')$$

$$T = 1.5T_c, T' = 0.75T_c, N_\tau = 48, N'_\tau = 96$$

- Output $\rho(\omega)$ larger depends on N_τ .

