Neural Quantum States advancements

for Hypernuclear physics

Andrea Di Donna June 26, 2024 andrea.didonna@unitn.it TIFPA - Trento University





1 Introduction

- 2 Interaction and Fit procedure
 - Microscopic Interaction: #EFT contact potentials
- 3 The NNQS variational approach
 - Step 0: Hidden Nucleon Wavefunction
 - Deep Sets
 - HN architecture Hypernuclei
 - Steps 1 and 2: Importance Sampling and Metropolis
 - Steps 1 and 2: Metropolis-Hastings Algorithm
 - Step 3: The Stochastic Reconfiguration Algorithm







Trento Institute for Fundamental Physics and Applications

4 Results

5 Conclusions

Open questions in Hypernuclear Physics:



■ Hyperon-Nucleon (YN) and Hyperon-Hyperon (YY) interactions are less well-understood than Nuclear forces. → Still these are relevant ...

■ At high densities the onset of hyperons in Neutron Stars → Hyperon puzzle

- Softening of the EoS due to reduced Pauli blocking.
- Observational data of 2 M_☉ neutron stars are in constrast with softening!
- To explain M/r ratio we have to introduce strongly repulsive *YNN* → **microscopic interaction**.

Interpretation of Astrophysical Observations

We want to understand how Hyperons affect the properties of the emitted gravitational waves, influencing observables such as tidal deformabilities during the merger of two NSs.



- Datas from new experiments may allow to constrain more efficiently the microscopic YN interaction at higher dentisies.
- To tackle these problems we need more accurate microscopic interaction models and computational tools.

Which microscopic-interaction model to choose?



Ab Initio description of Interactions

- Ab initio approaches derived from QCD \rightarrow
 - Relies on scarce experimental data to be constrained: Scattering parameters and BE to constrain two- and three-body potentials.
 - Provide controlled estimations of theoretical uncertainties expanding order by order.
 - 3 Disadvantages: After renormalization unresolved contact interactions must be extrapolated at $\lambda \rightarrow \infty$





- Predictivity: Ab initio approach can predict properties of systems that have not yet been observed.
- E.g.: Extending applicability of LQCD
 - Two- and three-body LECs from LQCD at fixed pion masses → predict four-body and higher-body interactions with EFT.



Hypernuclei are natural laboratories to study these interactions:

- To determine the hyperon-nucleon and hyperon-hyperon interaction potentials we need precise calculations of hypernuclear BE.
- Advancment in the computational approaches plays a significant role.

Objectives

Parametrize the wavefunction (variational state) using NNQS for single lambda hypernuclei:

$$^{A-1}Z + \Lambda \rightarrow {}^{A}_{\Lambda}Z$$

- Fit on few-body systems an improved leading-order (LO) interaction potential derived from # EFT.
- Predict Λ-separation and other observables for higher-A systems (⁷_ΛLi, ¹³_ΛC, ¹⁶_ΛO).

$$B_{\Lambda} = E(^{A-1}Z) - E(^{A}_{\Lambda}Z)$$

Andrea Di Donna | 5 of 39



Pionless Effective Field Theory (#EFT):

- Interaction potential derived from π EFT, valid for energies $Q < M_{hi} = m_{\pi} = 140$ MeV.
- Unresolved pions lead to spin-dependent contact potentials described by Low Energy Constants (LECs).

$$C_{IS}(\lambda)\delta_{\lambda}(\mathbf{x}_{ij}) = C_{IS}(\lambda)e^{-\frac{\lambda^{2}\mathbf{x}_{ij}^{2}}{4}}$$

Fitting Procedure:

Regulator cutoffs and LECs are fitted using SVM (Suzuki-Varga) and Gaussian Processes.

NN Potential:

 Fitted to neutron-proton (np) and neutron-neutron (nn) scattering lengths and effective ranges.

Three-Nucleon Force (3NF):

 Adjusted to reproduce the binding energies (BEs) of ³H and ⁴He.

$$V_{NN}(\mathbf{x}_{ij}) = \left(C_0(\lambda)^s P_{S_{lot}=0}^{2b} + C_0(\lambda)^t P_{S_{lot}=1}^{2b}\right) \delta_{\lambda}(\mathbf{x}_{ij})$$

$$V_{NNN}(\mathbf{x}_{ij}) = \mathcal{D}_0(\lambda) \sum_{i < j < k} \sum_{cyc} \delta_\lambda(\mathbf{x}_{ik}) \delta_\lambda(\mathbf{x}_{ij})$$

Extending π EFT to Hyperons



■ Introduction of ∧-Hyperons → Modify LO Interaction Potential:

Extending Pionless Effective Field Theory ($\not\!$ EFT) to hyperons requires introducing Λ -hyperon degrees of freedom ($m_{\Lambda} = 1116 \text{ MeV}$) into the Lagrangian density \mathcal{L} .

$$\mathcal{L} = N^{\dagger} \left(i \partial_0 + \frac{\nabla^2}{2M_N} \right) N + \Lambda^{\dagger} \left(i \partial_0 + \frac{\nabla^2}{2M_\Lambda} \right) \Lambda + \mathcal{L}_{2b} + \mathcal{L}_{3b} + \dots$$

$$egin{aligned} & V_{\Lambda N} = \sum_{IS} C^{IS}_{\lambda} \sum_{i < j} \mathcal{P}_{IS}(ij) \delta_{\lambda}(ec{r}_{ij}) \ & V_{\Lambda NN} = \sum_{IS} D^{IS}_{\lambda} \sum_{i < j} \mathcal{Q}_{IS}(ij\Lambda) \delta_{\lambda}(ec{r}_{i\Lambda}) \delta_{\lambda}(ec{r}_{j\Lambda}) \end{aligned}$$

• \mathcal{P}_{IS} and \mathcal{Q}_{IS} are projectors onto baryon doublets and triplets with isospin *I* and spin *S*.

Fitting Procedure:

- ΛN interaction is fitted to pΛ low energy scattering lengths and effective ranges Alexander et al.
- 2 ΛNN interaction is fitted to binding energies of ${}^{3}_{\Lambda}H$, ${}^{4}_{\Lambda}H_{S_{tot}=0}$, ${}^{4}_{\Lambda}H_{S_{tot}=1}$, and ${}^{5}_{\Lambda}He$.

$$\begin{array}{c} N & \Lambda \\ C_3 \rightarrow \begin{cases} S=0 \\ l=1/2 \\ C_4 \rightarrow \begin{cases} S=1 \\ l=1/2 \\ l=1/2 \end{cases} \\ \end{array} \begin{array}{c} N & \Lambda \\ N & D_2 \rightarrow \begin{cases} S=1/2 \\ l=0 \\ D_3 \rightarrow \begin{cases} S=3/2 \\ l=0 \\ D_4 \rightarrow \begin{cases} S=1/2 \\ l=1 \end{cases} \\ \end{array}$$



Overview:

- The Neural Network Quantum States (NNQS) approach (Carleo et al., 2017) is a form of unsupervised learning.
- Universal Approximation: Any type of variational state can be represented via NNQS.

Universal Approximation Theorem:
$$\Psi_{\mathcal{W}}(\mathbf{R}, \mathbf{S}) = \langle \mathbf{R}, \mathbf{S} \rangle$$

- Utilizes scalable neural networks for representation.
- Hidden Nucleon wavefunctions introduce dynamical correlations between particles and preserve statistical correlations through peculiar Network architectures.

Advantages:

- Easily applicable to different systems.
- Approximation error is no longer wavefunction-dependent for a given interaction.
- Less time-consuming and computationally demanding than other exact methods for $N \ge 5$.
- Computational cost scales polynomially with $\sim \alpha N^{5-6}$.
- GPU parallelization offer linear scaling with the number of GPU (Tested up to 22 GPU by 22 (Opt step for 160))
 - (Tested up to 32 GPUs \approx 2s/Opt. step for $^{16}_{\Lambda} \textit{O})$

Disadvantages:

EFT contact potentials δ_i(x_{ij}) introduce errors at large cut-offs in Monte Carlo evaluation of observables due to limited statistics in the interaction range.

The NNQS Variational Approach



NNQS as a Variational Method

Variational Principle:

$$\mathsf{E}_{V} = \frac{\langle \Psi_{\mathcal{W}} | \mathcal{H} | \Psi_{\mathcal{W}} \rangle}{\langle \Psi_{\mathcal{W}} | \Psi_{\mathcal{W}} \rangle} \ge \mathsf{E}_{0}$$

2 Iterative Optimization:

 $\frac{\delta E_V(\{\mathcal{W}\})}{\delta\{\mathcal{W}\}} = 0$

Defining an iterative procedure:

- Sampling the Wavefunction: Use *N* Markov Chains in parallel.
- Evaluating Observables and Gradients: Calculate expectation values using importance sampling.
- Parameter Update: Apply stochastic reconfiguration.





- Modeling the Wavefunction with the Hidden Nucleon Approach for Fermionic Systems:
 - Provides a systematic and extensible method for modeling antisymmetric wavefunctions through a single extended Slater determinant.
 - Reference: "Fermionic wave functions from neural-network constrained hidden states" by Carleo, Moreno et al. 2022

Constructing the Wavefunction:

- Introduces A_h virtual particles "hidden" DoFs in contrast to the real ones "visible" DoFs.
- **2** Hidden DoFs are represented by adding **hidden orbitals** $\chi_i(\tilde{x}_j)$.
- **3** Each virtual particle coordinate \tilde{x}_j is a bosonic function of all real particle coordinates: $\tilde{x}_j = f(\{X\})$ where $\{X\} = \{x_1, \dots, x_A\}$.

$$\Psi_{\rm HN}(\mathbf{X}) = \det \begin{pmatrix} \phi_{\rm v}(\mathbf{X}) & \phi_{\rm v}(f(\{\mathbf{X}\})) \\ \chi_{\rm h}(\mathbf{X}) & \chi_{\rm h}(f(\{\mathbf{X}\})) \end{pmatrix} = \det \begin{pmatrix} \phi_1(x_1) & \phi_1(x_2) & \phi_1(f(\{X\})) \\ \phi_2(x_1) & \phi_2(x_2) & \phi_2(f(\{X\})) \\ \chi_3(x_1) & \chi_3(x_2) & \chi_3(f(\{X\})) \end{pmatrix}$$

Visible orbitals on visible coordinates

Hidden orbitals on visible coordinates

Visible orbitals on hidden coordinates

Hidden orbitals on hidden coordinates



Question: Does extending the determinant preserve its antisymmetry under particle permutations? Expansion of the Determinant:

$$\begin{split} \phi_1(f(x)) \cdot (\phi_2(x_1)\chi_3(x_2) - \chi_3(x_1)\phi_2(x_2)) \\ & -\phi_2(f(x)) \cdot (\phi_1(x_1)\chi_3(x_2) - \chi_3(x_1)\phi_1(x_2)) \\ & +\chi_3(f(x)) \cdot (\phi_1(x_1)\phi_2(x_2) - \phi_2(x_1)\phi_1(x_2)) \end{split}$$

Comparison with Configuration Interaction (CI) Expansion:

$$|\Phi\rangle = C_0 |\Psi_0\rangle + \sum_{ra} C_a^r |\Psi_a^r\rangle + \sum_{\substack{a < b \\ a < b \\ r < s}} C_{ab}^{rs} |\Psi_{ab}^{rs}\rangle + \sum_{\substack{a < b < c \\ r < s < t}} C_{abc}^{rst} |\Psi_{abc}^{rst}\rangle + \dots$$

- Looks like a CI expansion with only one excited state (but it's more than that*).
- If each virtual coordinate $\tilde{x}_i = f(x)$ is a **permutation-invariant function (Network)** of the visible particle coordinates, the **antisymmetry** of the wavefunction is preserved.



Incorporating Dynamical Correlations with $f({x})$

The function $f({x})$ accounts for **Jastrow correlators**, introducing dynamical correlations into the wavefunction (**Isospin, Spin, Coulomb correlations** $x_i = [r_i, s_{z_i}, t_{z_i}]$).



Neural Network Implementation:

- Permutation Invariance: Introduced using the Deep Sets architecture.
- **Enhancing Correlations:** Improved through a **backflow transformation** of the coordinates {**x**}.

Step 0: HN Architecture - Visible Coordinate Sector

Phase-Amplitude representation of the Visible Coordinate orbitals:

The Visible coordinate sector involves both visible and hidden orbitals. The functions $\phi_a(x_i)$ and $\chi_a(x_i)$ are defined as:



$$\phi_{\alpha}(x_{i}) = e^{u_{\phi}^{\alpha}(x_{i}) + j \cdot v_{\phi}^{\alpha}(x_{i})}$$
$$\chi_{\alpha}(x_{i}) = e^{u_{\chi}^{\alpha}(x_{i}) + j \cdot v_{\chi}^{\alpha}(x_{i})}$$

Here, *u* and *v* are both feedforward neural networks (FFNNs) with only one hidden layer.



Single Particle FFNN Details:

- Input Nodes: 5 \rightarrow [$\mathbf{r}_i, \mathbf{s}_z, t_z$] where $\mathbf{r}_i \in \mathbb{R}^3$
- Non-linear Activation: Applied in hidden layers
- Output Nodes: 1 $\rightarrow \phi_{\alpha}(x_i)$





Phase-Amplitude representation of the Hidden Coordinate orbitals:

The Hidden coordinate sector involves both visible and hidden orbitals **evaluated on hidden coordinates**. The functions $\phi_a(x_i)$ and $\chi_a(x_i)$ are defined as:

det	$\phi_1(x_1)$	$\phi_1(x_2)$	$\phi_1(f(\{X\}))$
	$\phi_2(x_1)$	$\phi_2(x_2)$	$\phi_2(f(\{X\}))$
	$\chi_{3}(x_{1})$	$\chi_3(x_2)$	$\chi_{3}(f(\{X\}))$

$$\begin{split} \phi_i(f(\{\mathbf{X}\})) &= e^{\mathcal{U}^i_\phi(\{\mathbf{X}\}) + j \cdot \mathcal{V}^i_\phi(\{\mathbf{X}\})} \\ \chi_i(f(\{\mathbf{X}\})) &= e^{\mathcal{U}^i_\chi(\{\mathbf{X}\}) + j \cdot \mathcal{V}^i_\chi(\{\mathbf{X}\})} \end{split}$$

Deep Sets architecture:

Any permutation invariant neural network (\mathcal{U} and \mathcal{V}) can be sum-decomposed in the following way:

$$\mathcal{F}(\{\mathbf{X}\}) = \rho_{\mathcal{F}} \Big[\sum_{i \neq j} \phi_{\mathcal{F}}([\mathbf{x}_i, \mathbf{x}_j]) \Big] \qquad \mathcal{F} = \mathcal{U}, \mathcal{V}$$

- φ and ρ are both Neural Network, the sum operation destroy the order dependence of the network's inputs.
- This decomposition is called **Sum-Pooling**, since the aggregation function is $g(\cdot) = \sum_{x \in \mathfrak{X}}$.



■ Variational State of a Hypernucleus (single ∧ orbital):

$$\Psi_{HN} = \phi_{\Lambda}(\mathbf{x}_{\Lambda}, f(\{\mathbf{x}_{1}, \dots, \mathbf{x}_{A-1}, \mathbf{x}_{\Lambda}\})) \cdot \det_{A=1} \begin{vmatrix} \phi_{\nu}(\mathbf{X}) & \phi_{\nu}(f(\{\mathbf{X}\})) \\ \chi_{h}(\mathbf{X}) & \chi_{h}(f(\{\mathbf{X}\})) \end{vmatrix} \rightarrow \mathsf{Not sufficient!}$$



■ Variational State of a Hypernucleus (single ∧ orbital):

$$\Psi_{HN} = \phi_{\Lambda}(\mathbf{x}_{\Lambda}, f(\{\mathbf{x}_{1}, \dots, \mathbf{x}_{A-1}, \mathbf{x}_{\Lambda}\})) \cdot \det_{A^{-1}Z} \begin{vmatrix} \phi_{\mathsf{v}}(\mathbf{X}) & \phi_{\mathsf{v}}(f(\{\mathbf{X}\})) \\ \chi_{\mathsf{h}}(\mathbf{X}) & \chi_{\mathsf{h}}(f(\{\mathbf{X}\})) \end{vmatrix} \rightarrow \mathsf{Not sufficient!}$$

EXAMPLE: To represent AN correlations in the ³_AH mixed asimmetry spin state, the aggregator function for non-identical particles must be modified:

$$g(\mathcal{S}[\mathbf{x}_1,\ldots,\mathbf{x}_{A-1}],\mathbf{x}_A) = \left[\mathbf{x}_A,\sum_{i=1}^{A-1}\phi(\mathbf{r}_i,\mathbf{s}_i)\right]$$

Here, the coordinate of the Λ particle is concatenated with the sum pooling, so ΛN permutation invariance is not introduced.

Phase-Amplitude representation of ϕ_{Λ} : $\phi_{\Lambda}(g(\mathcal{S}(|\mathbf{x}_i|), \mathbf{x}_{\Lambda})) = e^{\left[i\rho_p\left(g(\mathcal{S}(|\mathbf{x}_i|), \mathbf{x}_{\Lambda})\right)\right]} \cdot e^{\left[\rho_a\left(g(\mathcal{S}(|\mathbf{x}_i|), \mathbf{x}_{\Lambda})\right)\right]}$



Extension to more than one As:

By combining the previous ideas, we generalize the Hidden Nucleon wavefunction to include multiple Λ particles:

$$\Psi_{\mathsf{HN}} = \det_{\Lambda} \begin{pmatrix} \phi_{\mathsf{V}}(\mathbf{X}_{\Lambda}) & \phi_{\mathsf{V}}\left(f\left(\{\mathbf{X}_{\Lambda}\}\right)\right) \\ \chi_{\mathsf{h}}(\mathbf{X}_{\Lambda}) & \chi_{\mathsf{h}}\left(f\left(\{\mathbf{X}_{\Lambda}\}\right)\right) \end{pmatrix} \cdot \det_{\mathcal{A} = I_{\mathcal{Z}}} \begin{pmatrix} \phi_{\mathsf{V}}(\mathbf{X}_{\Lambda}) & \phi_{\mathsf{V}}\left(f\left(\{\mathbf{X}_{\Lambda}\}\right)\right) \\ \chi_{\mathsf{h}}(\mathbf{X}_{\Lambda}) & \chi_{\mathsf{h}}\left(f\left(\{\mathbf{X}_{\Lambda}\}\right)\right) \end{pmatrix}$$

Where:

- \blacksquare det_{Λ} corresponds to the Λ hyperons.
- det_{A-1Z} corresponds to the nucleons (protons and neutrons). X_{Λ} and X_i are the backflow-transformed coordinates for the Λ particles and nucleons, respectively.



Observables Evaluation

Expectation values are computed through **importance sampling**. We rewrite the multidimensional integral for a generic observable *O* as:

 $O(\mathbf{V})$

$$O_{V} = \frac{\langle \Psi | O | \Psi \rangle}{\langle \Psi | \Psi \rangle} = \frac{\int d\mathbf{R} \langle \Psi | \mathbf{R}, \mathbf{S} \rangle \langle \mathbf{R}, \mathbf{S} | O | \Psi \rangle \frac{\langle \mathbf{R}, \mathbf{S} | \Psi \rangle}{\langle \mathbf{R}, \mathbf{S} | \Psi \rangle}}{\int d\mathbf{R} \langle \Psi | \mathbf{R}, \mathbf{S} \rangle \langle \mathbf{R}, \mathbf{S} | \Psi \rangle} \stackrel{\mathbf{X} = [\mathbf{R}, \mathbf{S}]}{=} \frac{\int d\mathbf{R} |\Psi(\mathbf{X})|^{2} O_{L}(\mathbf{X})}{\int d\mathbf{R} |\Psi(\mathbf{X})|^{2}} = \int d\mathbf{R} P(\mathbf{X}) O_{L}(\mathbf{X})$$

Definitions:

• Local observable:
$$O_L(\mathbf{X}) = \frac{O\Psi(\mathbf{X})}{\Psi(\mathbf{X})}$$

- Probability density: $P(\mathbf{X}) = \frac{|\Psi(\mathbf{X})|^2}{\int d\mathbf{R} |\Psi(\mathbf{X})|^2}$
- \rightarrow Sampled trough Metropolis Hastings Algorithm

Monte Carlo Estimation:

$$O_V = rac{1}{\mathcal{N}_{ ext{walker}}} \sum_{s=1}^{\mathcal{N}_{ ext{walker}}} O_L(\mathbf{X}_s)$$

Statistical Uncertainty:

$$\sigma_{\mathcal{O}_{V}} = \sqrt{\frac{1}{\mathcal{N}_{\text{walker}} - 1} \sum_{s=1}^{\mathcal{N}_{\text{walker}}} \left(O_{L}(\mathbf{X}_{s}) - O_{V} \right)^{2}}$$

Steps 1 and 2: Metropolis-Hastings Algorithm



Objective: To sample the probability distribution: $P(\mathbf{X}) = \frac{|\Psi_T(\mathbf{X})|^2}{\int d\mathbf{R} |\Psi_T(\mathbf{X})|^2}$ **Metropolis-Hastings Algorithm:**

- Based on the concept of a random walk forming a Markov chain with transition matrix Π.
- The transition probability is given by:

$$\mathcal{P}(X_{i+1} = x_{i+1} | X_i = x_i) = \Pi(x_i, x_{i+1}) = q(x_{i+1} | x_i) r(x_{i+1} | x_i)$$

Proposal Step:

Generate a new state:

$$x_{i+1} = x_i + \zeta, \quad \zeta \sim N(0, \sigma^2)$$

Compute the acceptance ratio: $r(x_{i+1}|x_i) = \min\left(1, \frac{P(x_{i+1})q(x_i|x_{i+1})}{P(x_i)q(x_{i+1}+\tau|x_i)}\right)$



Multiple Particle Diffusion:



Sampling Procedure:

- 1 Allow the system to thermalize.
- 2 Collect Navg samples, spaced by
 - \mathcal{N}_{void} steps: reduce autocorrelation





Overview:

- Stochastic Reconfiguration (SR): Introduced by S. Sorella (2005).
- In the context of Variational Monte Carlo (VMC) SR is equivalent to performing an imaginary-time evolution in parameter space.
- It is related to the Natural Gradient Descent method (Amari et al.).

Imaginary-Time Evolution in Parameter Space:

The imaginary-time evolution operator is approximated as ($\tau \approx 0$):

$$e^{-H au} pprox 1 - H au$$

• Acting on the trial wavefunction $|\Psi_T(\mathcal{W})\rangle$, we have:

$$(1 - H\tau) |\Psi_{\mathsf{T}}(\mathcal{W})\rangle \approx |\Psi_{\mathsf{T}}(\mathcal{W} + \Delta \mathcal{W})\rangle = \Delta \mathcal{W}_{\mathsf{0}} |\Psi_{\mathsf{T}}(\mathcal{W})\rangle + \sum \Delta \mathcal{W}_{j} O^{j} |\Psi_{\mathsf{T}}(\mathcal{W})\rangle$$

• Where:
$$O^i | \Psi_T(\mathcal{W}) \rangle = \left| \frac{\partial}{\partial \mathcal{W}_i} \Psi_T(\mathcal{W}) \right\rangle$$

Deriving the SR Equations:

• Multiply both sides from the left by $\frac{\langle \Psi_T(W)|}{\langle \Psi_T(W)|\Psi_T(W)\rangle}$ and $\frac{\langle \Psi_T(W)|O^i}{\langle \Psi_T(W)|\Psi_T(W)\rangle}$,



Solving for Parameter Updates:

Solving the first equation for ΔW_0 and substituting into the second equation yields:

$$\underbrace{\left(\langle H \rangle \langle O^{i} \rangle - \langle H O^{i} \rangle\right)}_{-\frac{1}{2}G_{i}} \tau = \sum_{j} \Delta \mathcal{W}_{j} \underbrace{\left(\langle O^{i} O^{j} \rangle - \langle O^{i} \rangle \langle O^{j} \rangle\right)}_{\mathcal{S}_{ij}}$$

- Defining quantities Evaluated via Importance Sampling:
 - Gradient:

$$G_{i} = 2\left(\langle HO^{i}\rangle - \langle H\rangle\langle O^{i}\rangle\right) = -2\frac{\partial E(\mathcal{W})}{\partial \mathcal{W}_{i}}$$

Quantum Geometric Tensor (QGT):

$$S_{ij} = \langle O^i O^j \rangle - \langle O^i \rangle \langle O^j \rangle$$

The update rule for the parameters becomes:

$$\mathcal{W}_{i}^{n+1} = \mathcal{W}_{i}^{n} + \Delta \mathcal{W}_{i}^{n} = \mathcal{W}_{i}^{n} - \frac{1}{2}\tau \sum_{j} (\underbrace{\mathcal{S}_{ij}^{n} + \epsilon \delta_{ij}}_{\text{avoid saddle points}})^{-1} G_{j}^{n}$$

- **The term** $\epsilon \delta_{ij}$ is added to avoid saddle points and improve numerical stability.
- Note: The QGT resembles a covariance matrix.

Fisher Information and Quantum Geometric Tensor



Classical Information Theory:

- The Riemannian structure of the parameter space \mathcal{P} of a statistical model $P(\mathbf{x}|\mathbf{w})$, which depends on parameters \mathbf{w} , is defined by the **Fisher Information**:
- Covariance of the derivative of the log-likelihood (Score Function)

 $g_{ij}(\mathbf{w}) = \mathbb{E}_{P(\mathbf{x}|\mathbf{w})} \left[\frac{\partial \log P(\mathbf{x}|\mathbf{w})}{\partial w_i} \frac{\partial \log P(\mathbf{x}|\mathbf{w})}{\partial w_j} \right]$

Curvature of the log-likelihood

$$g_{ij}(\mathbf{w}) = -\mathbb{E}_{P(\mathbf{x}|\mathbf{w})} \left[\frac{\partial^2}{\partial w_i \partial w_j} \log P(\mathbf{x}|\mathbf{w}) \right]$$

Quantum Information Theory:

The Fubini-Study metric defines the distance between infitesimally close quantum states:

$$d_{\mathsf{FS}}^{2}[\Psi_{V}(\mathbf{X}|\mathbf{w}),\Psi_{V}(\mathbf{X}|\mathbf{w}+d\mathbf{w})]\approx\sum_{i}\mathcal{S}_{ij}(\mathbf{w})\,dw_{i}\,dw_{j}$$

• If Ψ is defined over a basis: $|\Psi(\mathbf{X}|\mathbf{w})\rangle = \sum_{\mathbf{X}} \sqrt{P(\mathbf{X}|\mathbf{w})} |\mathbf{X}\rangle$ Then it can be shown that:

 $\mathcal{S}_{ij}(\mathbf{w}) = rac{1}{4}g_{ij}(\mathbf{w})$ Quantum Natural Gradient - Carleo et al. (Quantum, May 2020), page 10

Interpretations:

- A sharp Fisher Information (high curvature $\partial^2_{\mathbf{w}_i}$) $\rightarrow \Psi$ (or its walker's sample) is relevantly determined from parameter \mathbf{w}_i .
- We suppress the variation of such parameters: $G_i^n \to \sum_j (S_{ij}^n)^{-1} G_i^n$.

Combining SR with RMSProp:



- In RMSProp, the gradient expresses the **acceleration** in the parameter space.
- The S matrix (Quantum Geometric Tensor) is regularized using running averages of the squared gradients to improve numerical stability.

Update Rules:

Compute running averages:

$$\mathbf{m}^{n+1} = \beta \, \mathbf{m}^n + (1 - \beta) \, (\mathbf{G}^n \odot \mathbf{G}^n)$$

Regularize S matrix:

$$S_{ij}^{n} + \epsilon \, \delta_{ij} \rightarrow S_{ij}^{n} + \epsilon \, \text{diag} \left(\sqrt{\mathbf{m}^{n}} + 10^{-8} \right)$$

Explanation:

The hyperparameter ε adds an L² penalty term to the solution of the linear system used to determine ΔW:

$$\|\Delta \mathcal{W} S - \mathbf{G}\| = \|\epsilon \Delta \mathcal{W}\|$$

 This regularization helps to avoid issues with ill-conditioned S matrices and prevents large, unstable parameter updates.



Let's see some results...

Andrea Di Donna | 23 of 39







 ${}^{4}_{\Lambda}H_{S_{tot}=0}$ Projectors





 ${}^{4}_{\Lambda}H_{S_{tot}=0}$ Density





















Andrea Di Donna | 30 of 39











To test the stability of the AN-ANN interaction each BE is evaluated for 10 different potentials



Hypernuclear **BE**



Hypernuclear RMS radii



A – separation Energies



NNQS shows great flexibility in modeling hypernuclear bound states.

- NQS Variational State → match with accuracy the binding energy and quantum numbers of studied hypernuclear systems.
- Fitted interaction: Improved LO guarantes the desired accuracy.

Other advancements in the field: (A. Lovato, A. Gnech)

Shell structure is emerging even if not encoded in the system https://arxiv.org/pdf/2308.16266

Outlook:

- 1 Moving to NLO and restore cutoff dependence.
- 2 Extension of calculations to larger mass hypernuclei.
- 3 Hypernuclear matter \rightarrow EoS



NNQS shows great flexibility in modeling hypernuclear bound states.

- NQS Variational State → match with accuracy the binding energy and quantum numbers of studied hypernuclear systems.
- Fitted interaction: Improved LO guarantes the desired accuracy.
- Other advancements in the field: (A. Lovato, A. Gnech)
 - Shell structure is emerging even if not encoded in the system https://arxiv.org/pdf/2308.16266

Outlook:

- 1 Moving to NLO and restore cutoff dependence.
- 2 Extension of calculations to larger mass hypernuclei.
- 3 Hypernuclear matter \rightarrow EoS

Thank you!

Step 0: Pre-processing (Backflow) of Coordinates via MPNN UNIVERSITÀ DI TRENTC

Backflow Transformation for Single Particle Coordinates:

Neural Network Interpretation:

(MPNN).

Modifies particle coordinates so that the effective position of a particle depends on its own position and the positions of all other particles.



Reference: MPNN NQS for the Homogeneous Electron Gas - Lovato, Carleo, Kim, Pescia, Nys (2023), arXiv:2305.07240v3

Riferimenti I





Gal, A., Hungerford, E. V., & Millener, D. J. (2016).

Strangeness in nuclear physics. Reviews of Modern Physics, 88(3), 035004.



Lonardoni, D., Gandolfi, S., & Pederiva, F. (2015).

Hyperon Puzzle: Hints from Quantum Monte Carlo Calculations. *Physical Review C*, 87(4), 041303(R).



Abbott, B. P., et al. (2017).

GW170817: Observation of Gravitational Waves from a Binary Neutron Star Inspiral. *Physical Review Letters*, 119(16), 161101.



Haidenbauer, J., et al. (2013).

Hyperon-nucleon interaction at next-to-leading order in chiral effective field theory. Nuclear Physics A, 915, 24-58.



Lonardoni, D., et al. (2014).

Hyperon-Nucleon Interactions from Quantum Monte Carlo Calculations. *Physical Review Letters*, 113(13), 142301.



Hiyama, E., & Yamamoto, Y. (2012).

Recent progress in studies of baryon-baryon interactions and hypernuclei. Progress in Particle and Nuclear Physics, 63(2), 339-395.



Epelbaum, E., Hammer, H.-W., & Meißner, U.-G. (2009).

Modern theory of nuclear forces. Reviews of Modern Physics, 81(4), 1773.