



國科大杭州高等研究院
Hangzhou Institute for Advanced Study, UCAS



Insights into Neutron Star Equation of State by Machine Learning

By Lingjun Guo (郭凌君)

Jilin University

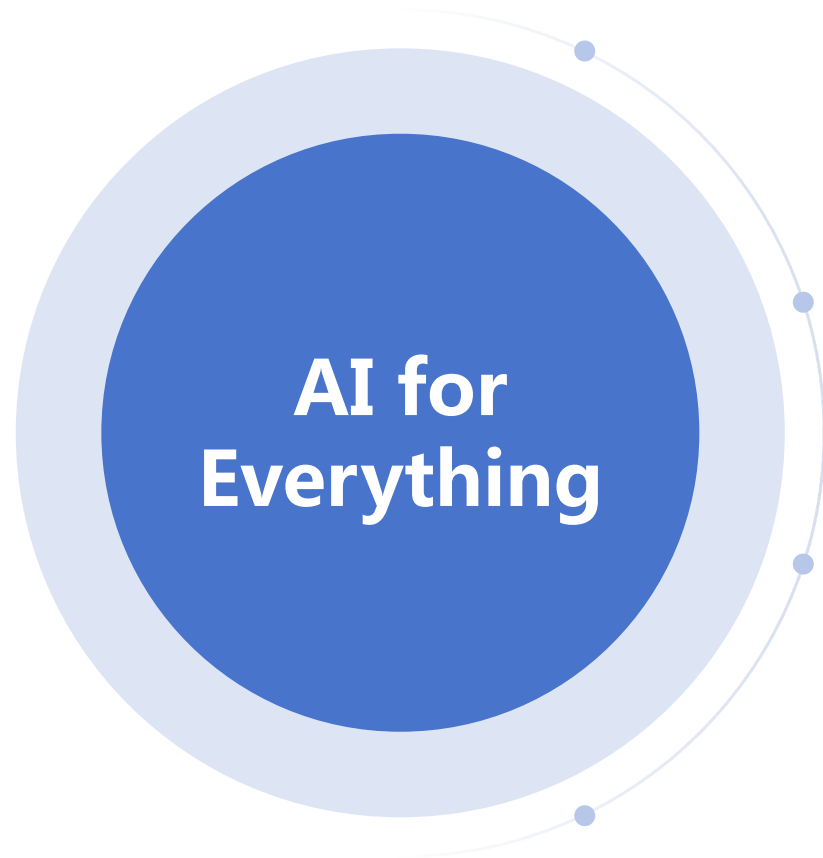
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Guo L J, Xiong J Y, Ma Y, et al. Insights into neutron star equation of state by machine learning[J]. The Astrophysical Journal, 2024, 965(1): 47.

In preparation for 23-par AI model

In collaboration with Yao Ma (马焱), Jiaying Xiong (熊佳颖), Yongliang Ma (马永亮)

Artificial Intelligence



Physics

2024 Nobel Prize

Chemistry

2024 Nobel Prize

AutoDriving

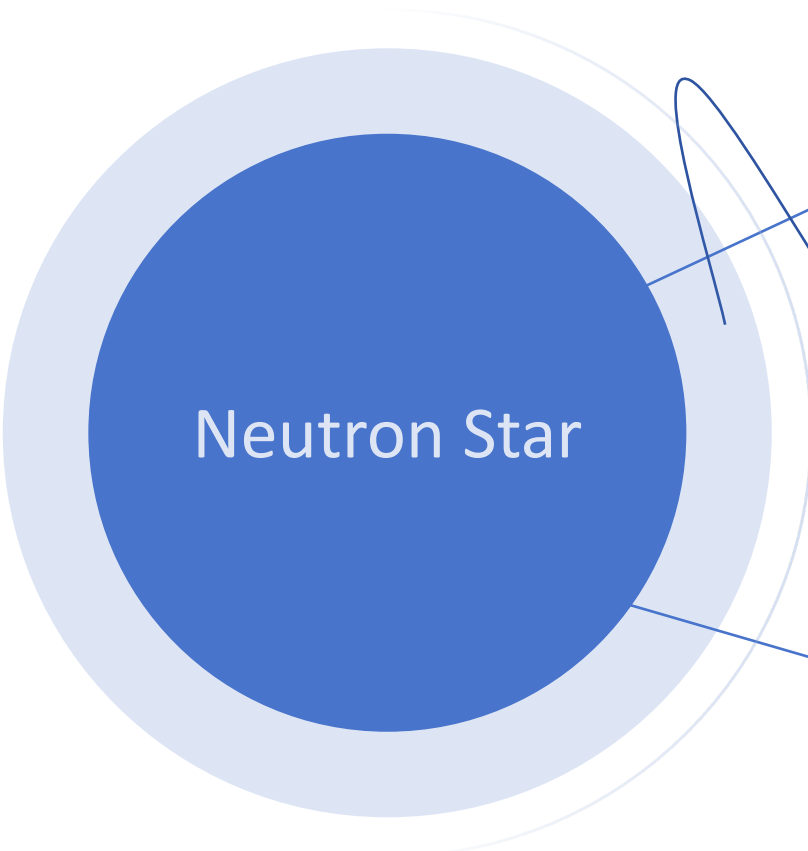
End-to-End training

ChatGPT

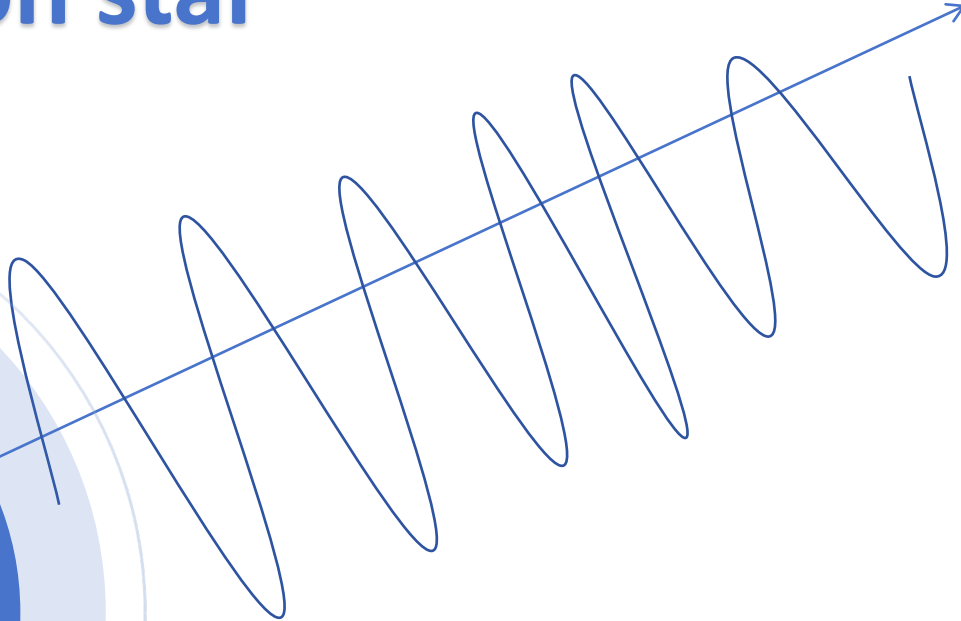
World model

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Observing Neutron star



Neutron Star



Ligo, Vrigo

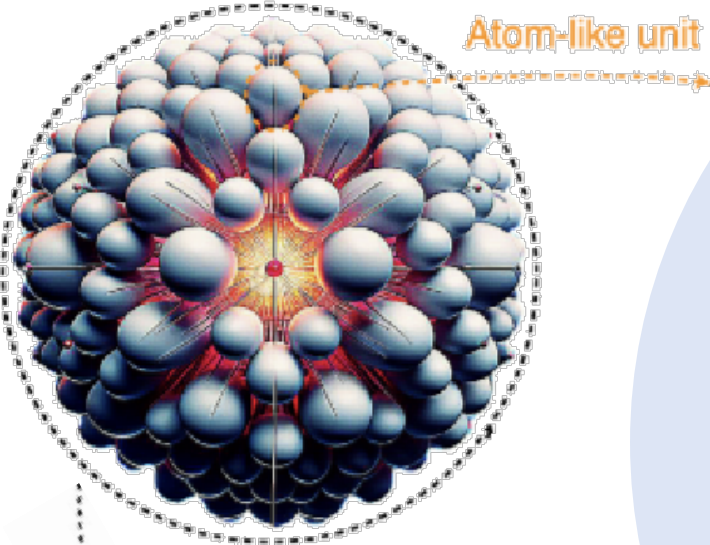
M-R Relations

Tidal deformation

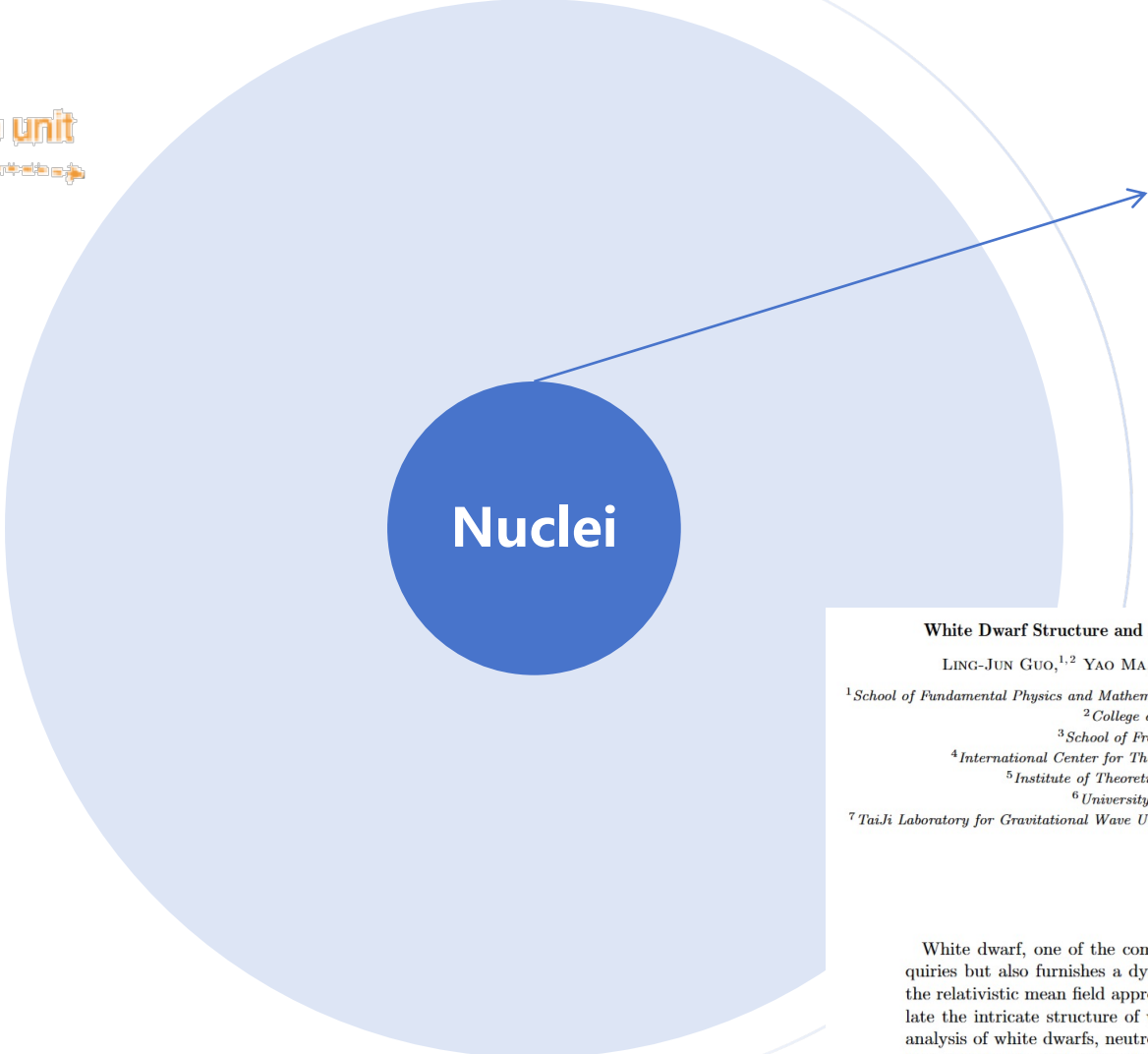
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Telescope

From nuclei to white dwarf



White Dwarf Star



$$\begin{aligned}
 n_0 &\rightarrow 0.155 \pm 0.050 \text{ (fm}^{-3}\text{)} \\
 E_0(n_0) &\rightarrow -15.0 \pm 1.0 \text{ (MeV)} \\
 E_{\text{sym}}(n_0) &\rightarrow 30.9 \pm 1.9 \text{ (MeV)} \\
 K_0 &\rightarrow 230 \pm 30 \text{ (MeV)} \\
 L_0 &\rightarrow 52.5 \pm 17.5 \text{ (MeV)} \\
 J_0 &\rightarrow -700 \pm 500 \text{ (MeV)}
 \end{aligned}$$

White Dwarf Structure and Binary Inspiral Gravitational Waves from Quantum Hadrodynamics

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ABSTRACT

White dwarf, one of the compact objects in the universe, is not only pivotal for astrophysical inquiries but also furnishes a dynamic arena for nuclear physics exploration. In this work, we extend the relativistic mean field approach using a Walecka-type quantum hadrodynamics model to encapsulate the intricate structure of white dwarfs. This methodological advancement facilitates a cohesive analysis of white dwarfs, neutron stars, and the nuclear pasta within a unified theoretical framework. By meticulously calibrating the model parameters to nuclear matter properties, we successfully replicate the structures of various nuclei, such as ⁴He, isotopes of C, and ¹⁶O. Subsequently, we predict the properties of white dwarfs composed of atom-like units and the gravitational waves stemming from binary white dwarf inspirals incorporating tidal deformability contributions up to the 2.5 post-Newtonian order. These results shed light on the structure of white dwarfs and offer more clues for future gravitational wave detection.

The Journey of a Model

Lagrangian:

$$\begin{aligned} \mathcal{L}_{\text{RMF}} = & \bar{\psi} \left[i\gamma_{\mu} \partial^{\mu} - M - g_{\sigma} \sigma - g_{\omega} \gamma_{\mu} \omega^{\mu} - g_{\rho} \gamma_{\mu} \tau_a \rho^{a\mu} - e\gamma_{\mu} \frac{1 - \tau_3}{2} A^{\mu} \right] \psi \\ & + \frac{1}{2} \partial_{\mu} \sigma \partial^{\mu} \sigma - \frac{1}{2} m_{\sigma}^2 \sigma^2 - \frac{1}{3} g_2 \sigma^3 - \frac{1}{4} g_3 \sigma^4 \\ & - \frac{1}{4} W_{\mu\nu} W^{\mu\nu} + \frac{1}{2} m_{\omega}^2 \omega_{\mu} \omega^{\mu} + \frac{1}{4} c_3 (\omega_{\mu} \omega^{\mu})^2 \\ & - \frac{1}{4} R_{\mu\nu}^a R^{a\mu\nu} + \frac{1}{2} m_{\rho}^2 \rho_{\mu}^a \rho^{a\mu} - \frac{1}{4} F_{\mu\nu} F^{\mu\nu}, \end{aligned}$$

where

$$\begin{aligned} W^{\mu\nu} &= \partial^{\mu} \omega^{\nu} - \partial^{\nu} \omega^{\mu}, \\ R^{a,\mu\nu} &= \partial^{\mu} \rho^{a\nu} - \partial^{\nu} \rho^{a\mu} + g_{\rho} \epsilon^{abc} \rho^{b\mu} \rho^{c\nu}, \\ F^{\mu\nu} &= \partial^{\mu} A^{\nu} - \partial^{\nu} A^{\mu}. \end{aligned}$$

RMF



EC

$$\begin{aligned} m_{\sigma}^2 \sigma + g_2 \sigma^2 + g_3 \sigma^3 &= -g_{\sigma} (\rho_{n,s} + \rho_{p,s}), \\ m_{\omega}^2 \omega + c_3 \omega^3 &= g_{\omega} (\rho_p + \rho_n), \quad \rho_{n(p),s} = \frac{m_N^{*3}}{\pi^2} \int_0^{t_{n(p)}} dx \frac{x^2}{\sqrt{1+x^2}} \\ m_{\rho}^2 \rho &= g_{\rho} (\rho_p - \rho_n), \quad = \frac{m_N^{*3}}{\pi^2} \left[\frac{1}{2} (t_{n(p)} \sqrt{1+t_{n(p)}^2} - \text{arcsinh} t_{n(p)}) \right] \end{aligned}$$

TOV:

$$\begin{aligned} \frac{dP}{dr} &= (\rho(1 + \epsilon) + p) \frac{m + 4\pi r^3 p}{r(r - 2m)}, \\ \frac{dm(r)}{dr} &= 4\pi \rho (1 + \epsilon) r^2. \end{aligned}$$



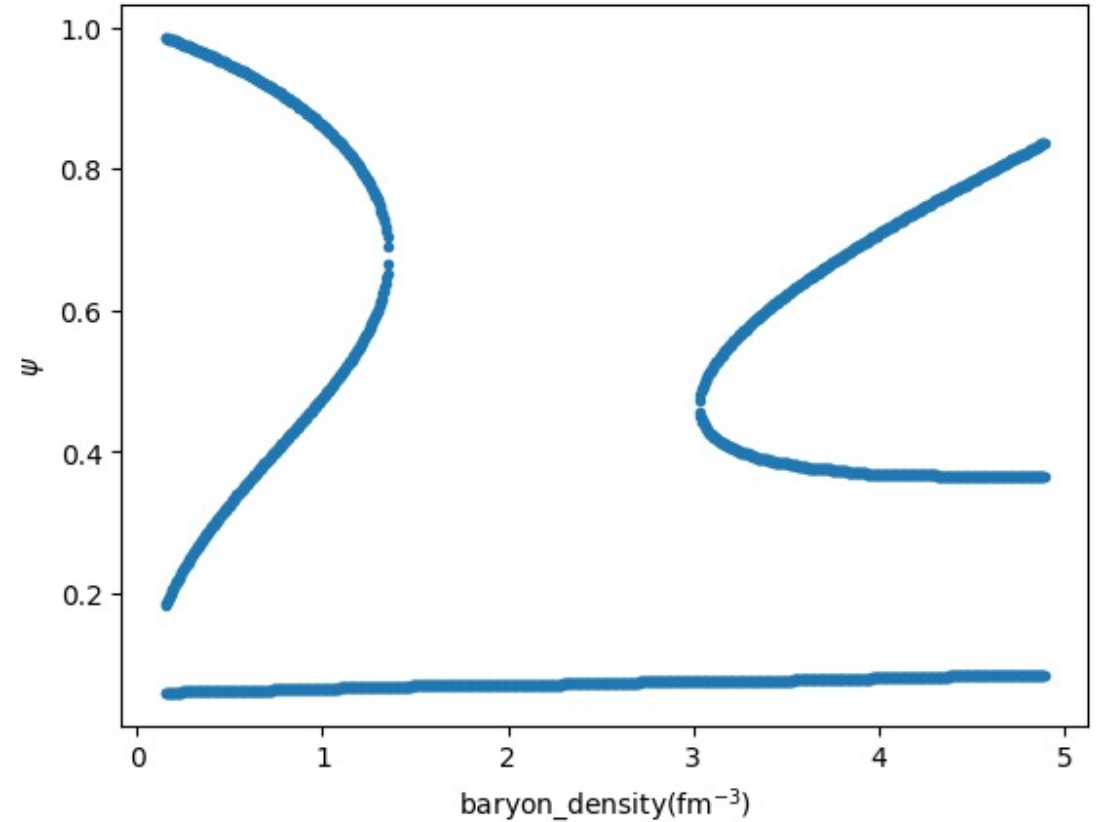
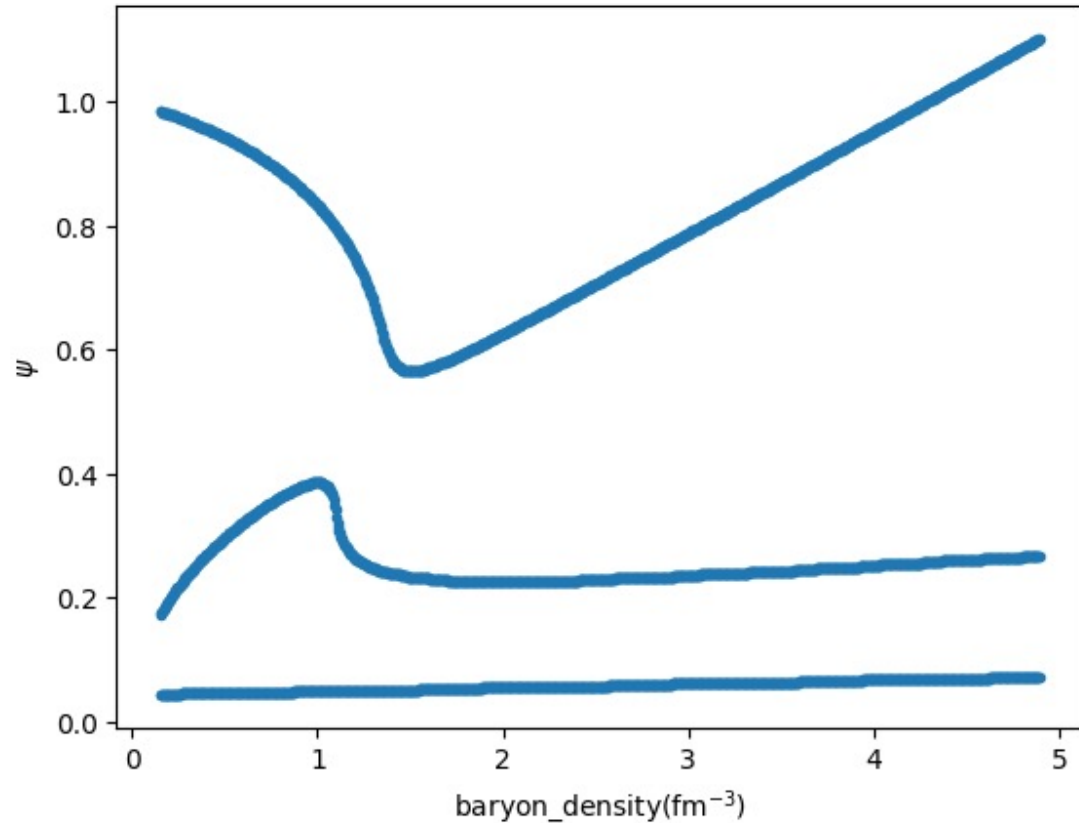
EOS:

$$\begin{aligned} \mathcal{E} &= \frac{m_N^{*4}}{8\pi^2} \sum_{i=n,p} \left[t_i \sqrt{t_i^2 + 1} (1 + 2t_i^2) - \text{arcsinh} t_i \right] + \\ & g_{\omega} \omega (\rho_n + \rho_p) + g_{\rho} \rho (\rho_p - \rho_n) + \\ & \frac{1}{2} m_{\sigma}^2 \sigma^2 + \frac{1}{3} g_2 \sigma^3 + \frac{1}{4} g_3 \sigma^4 - \\ & \frac{1}{2} m_{\omega}^2 \omega^2 - \frac{1}{4} c_3 \omega^4 - \frac{1}{2} m_{\rho}^2 \rho^2. \\ P &= -\mathcal{E} + \rho_N \frac{d\mathcal{E}}{d\rho_N} \end{aligned}$$



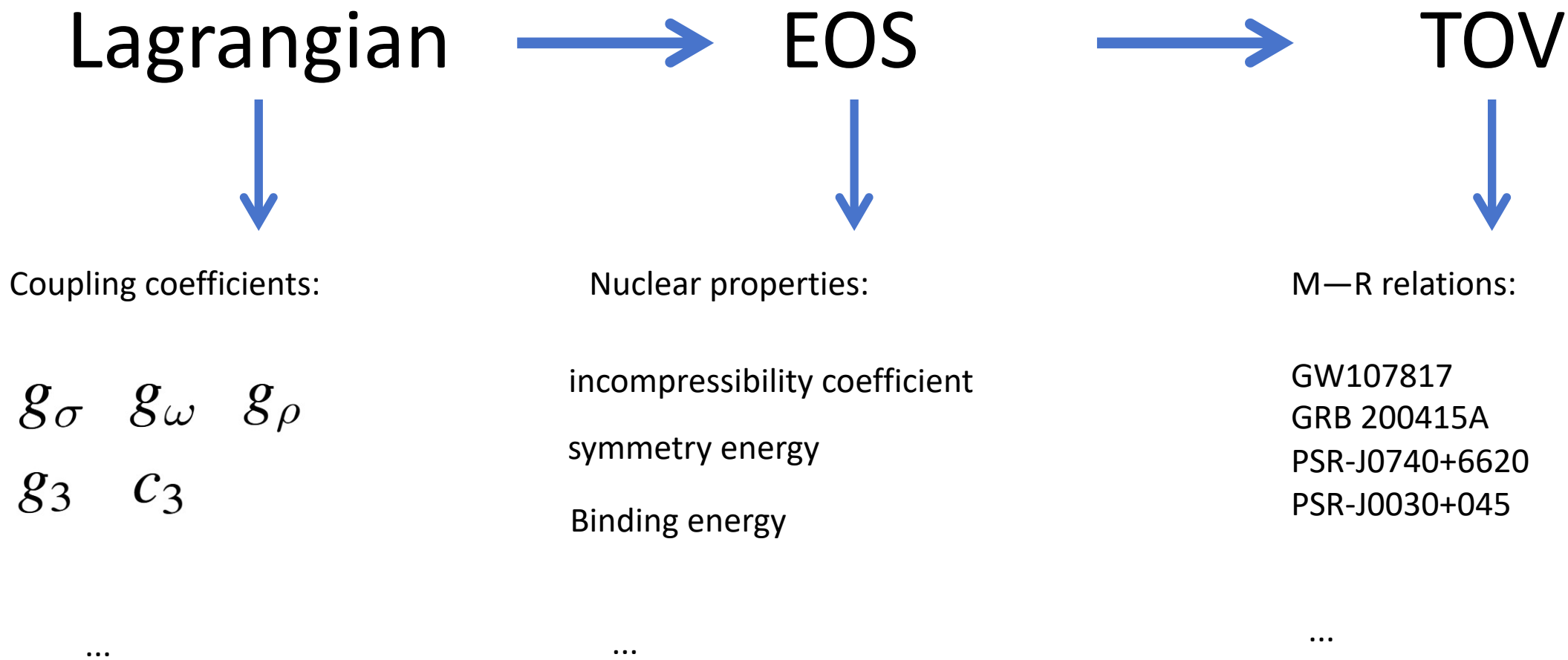
The Journey of a Model

Multi solution problem



The Journey of a Model

Coupling coefficients



Bayesian inference

g_σ g_ω g_ρ
 g_3 c_3

$$P(H | E) = \frac{P(E | H) \cdot P(H)}{P(E)}$$

$$p(\theta | \mathbf{X}, \alpha) = \frac{p(\mathbf{X} | \theta)p(\theta | \alpha)}{p(\mathbf{X} | \alpha)} \propto p(\mathbf{X} | \theta)p(\theta | \alpha)$$

Markov Chain Monte Carlo, MCMC
Variational Inference

emcee、PyMC3、ArviZ

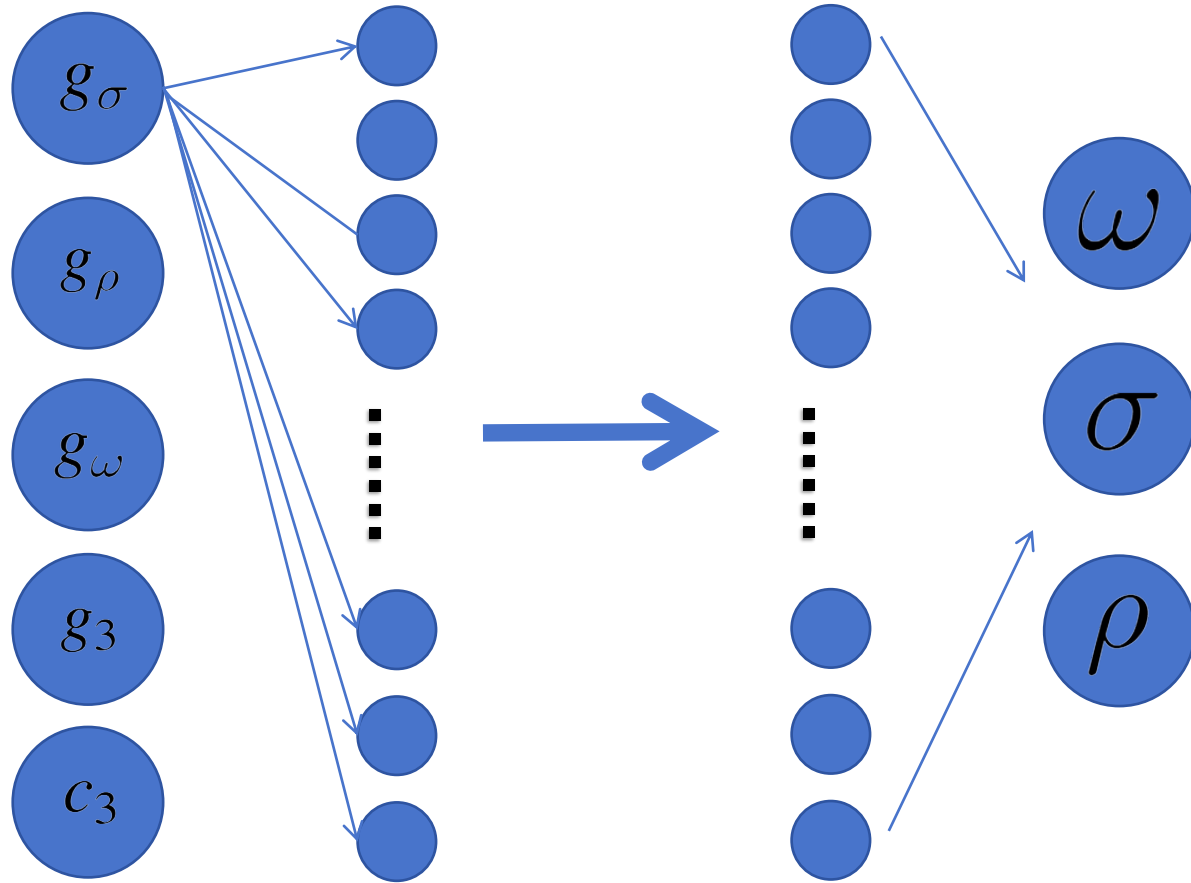
Drischler, C., Furnstahl, R. J., Melendez, J. A., & Phillips, D. R. (2020). How well do we know the neutron-matter equation of state at the densities inside neutron stars? A Bayesian approach with correlated uncertainties. *Physical Review Letters*, 125(20), 202702.

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doi: [10.3847/1538-4357/acc4be](https://doi.org/10.3847/1538-4357/acc4be)

Han, M.-Z., Jiang, J.-L., Tang, S.-P., & Fan, Y.-Z. 2021, *Astrophys. J.*, 919, 11,
doi: [10.3847/1538-4357/ac11f8](https://doi.org/10.3847/1538-4357/ac11f8)

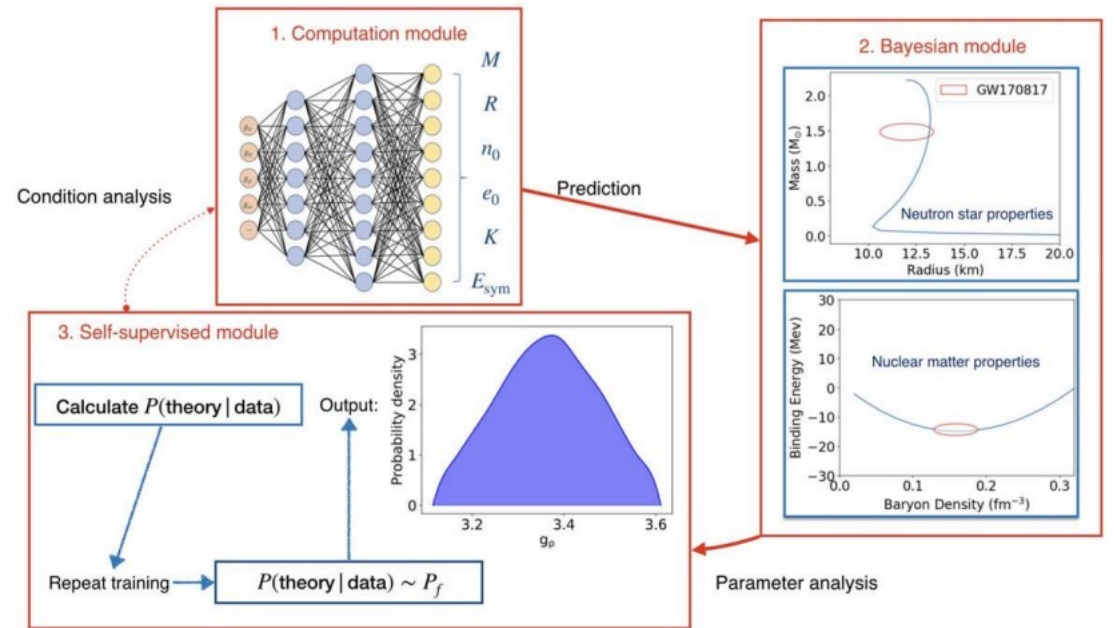
The Journey of a Model

Machine Learning Approach

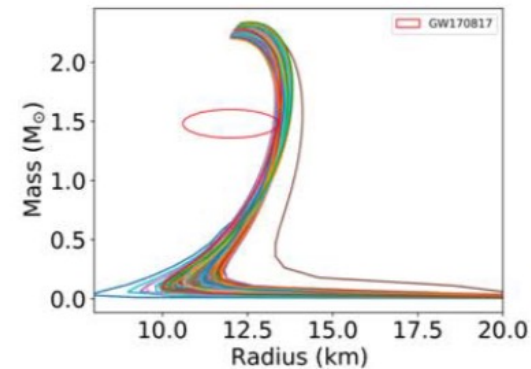
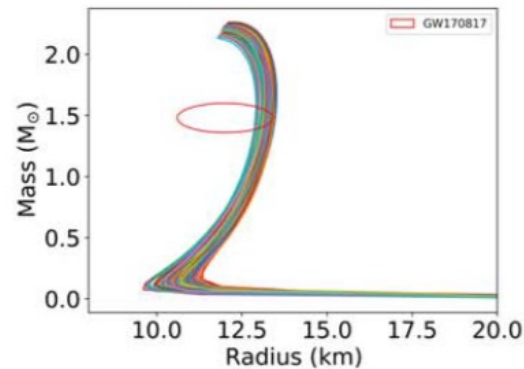
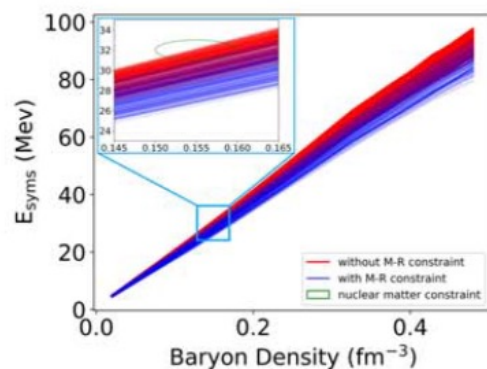
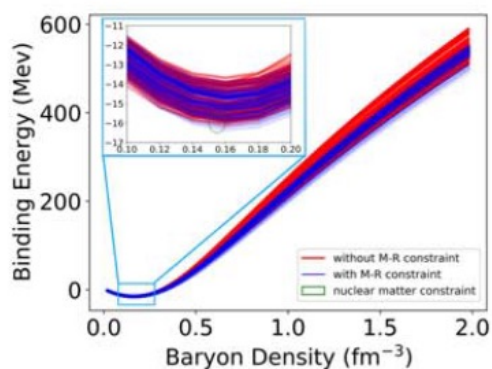
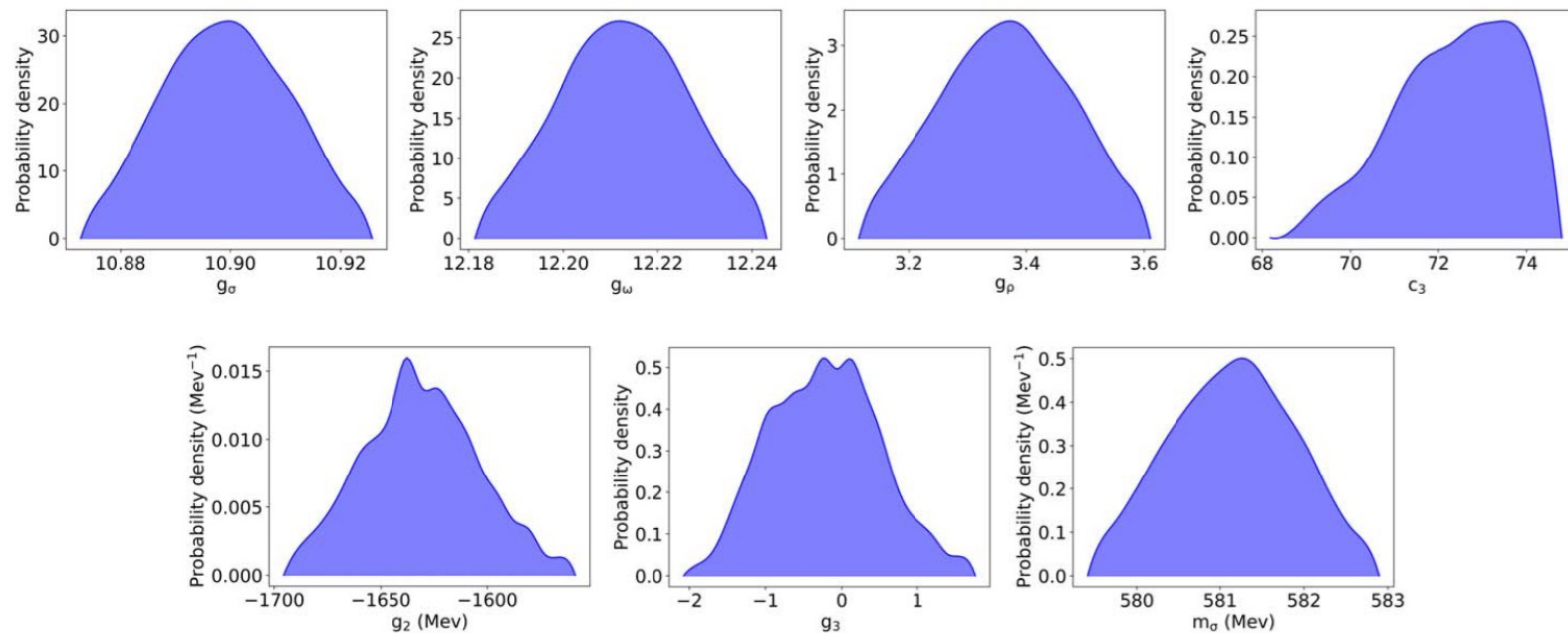


$$f_{\text{loss},\sigma} = \left[m_\sigma^2 \sigma + g_2 \sigma^2 + g_3 \sigma^3 + g_\sigma (\rho_{n,s} + \rho_{p,s}) \right]^2$$

$$f_{\text{loss},\omega} = \left[m_\omega^2 \omega + c_3 \omega^3 - g_\omega (\rho_p + \rho_n) \right]^2$$



Bayesian Parameter Estimation



(a) e_0 with NM property constraints.

(b) E_{syms} with NM property constraints.

(c) MR relations with MR constraints.

(d) MR relations without MR constraints.

21-parameters-model for AI

$$\mathcal{L}_N = \bar{\Psi}(i\gamma^\mu \partial_\mu - m_N)\Psi$$

$$\mathcal{L}_\sigma = \frac{1}{2}(\partial_\mu \sigma \partial^\mu \sigma - m_\sigma^2 \sigma^2) - \frac{1}{3}g_2 \sigma^3 - \frac{1}{4}g_3 \sigma^4 - \frac{1}{2}g_4 \sigma^2 \omega^\mu \omega_\mu - \frac{1}{2}g_5 \sigma^2 \text{Tr}(\vec{\rho}^\mu \cdot \vec{\rho}_\mu)$$

$$\mathcal{L}_\omega = -\frac{1}{4}\Omega^{\mu\nu}\Omega_{\mu\nu} + \frac{1}{2}m_\omega^2 \omega^\mu \omega_\mu + \frac{1}{4}c_3(\omega^\mu \omega_\mu)^2 + \frac{1}{2}c_4 \omega^\mu \omega_\mu \text{Tr}(\vec{\rho}^\mu \cdot \vec{\rho}_\mu)$$

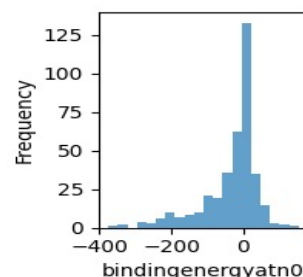
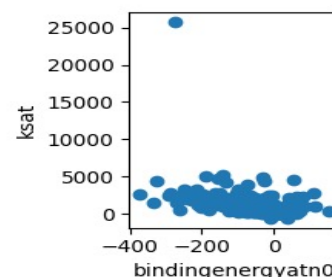
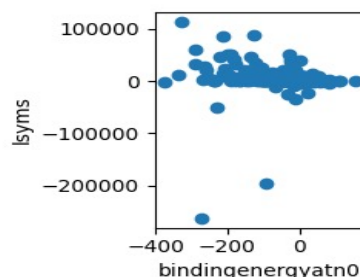
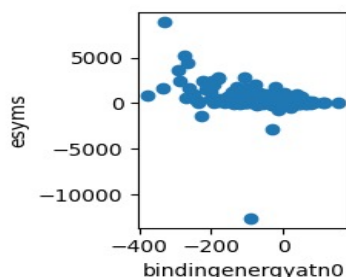
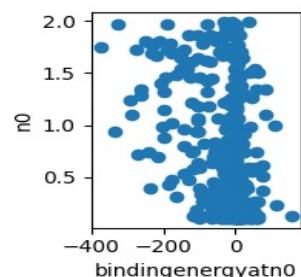
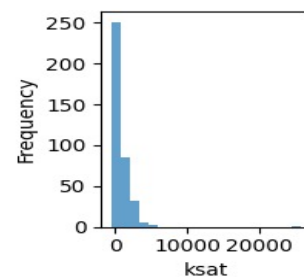
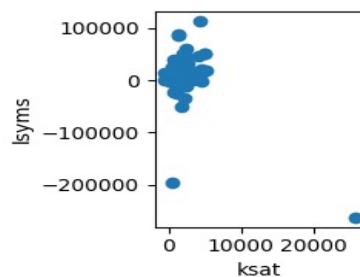
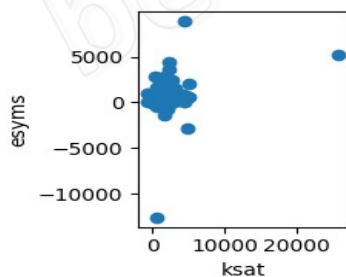
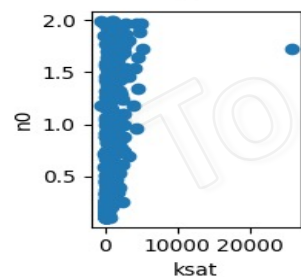
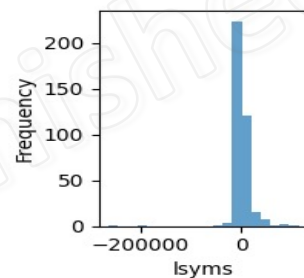
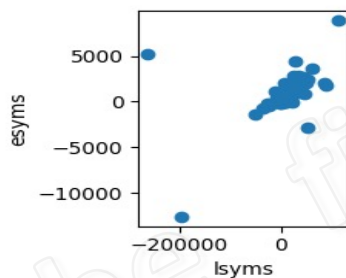
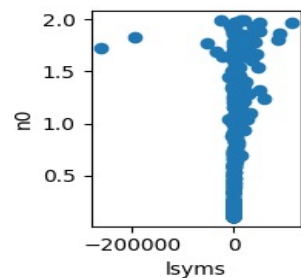
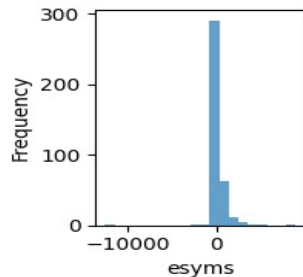
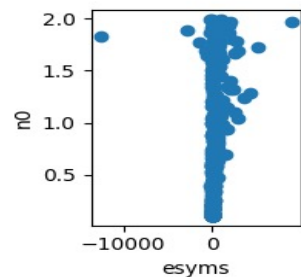
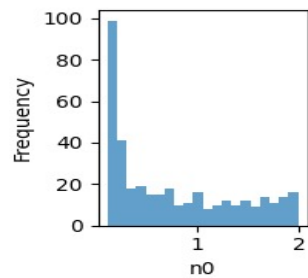
$$\mathcal{L}_\rho = -\frac{1}{4}\text{Tr}(P^{\mu\nu} \cdot P_{\mu\nu}) + \frac{1}{2}m_\rho^2 \text{Tr}(\vec{\rho}^\mu \cdot \vec{\rho}_\mu) + \frac{1}{4}d_3 \text{Tr}[(\vec{\rho}^\mu \cdot \vec{\rho}_\mu)^2]$$

$$\begin{aligned} \mathcal{L}_{a_0} = & \frac{1}{2}\text{Tr}(\partial_\mu \vec{a}_0 \partial^\mu \vec{a}_0 - m_{a_0}^2 \vec{a}_0 \vec{a}_0) + \frac{1}{4}b_3 \text{Tr}[(\vec{a}_0 \vec{a}_0)^2] + \frac{1}{2}b_4 \text{Tr}[(\vec{a}_0 \vec{a}_0)(\vec{\rho}^\mu \vec{\rho}_\mu)] \\ & + \frac{1}{2}b_6 \text{Tr}[\vec{a}_0 \vec{a}_0] \sigma^2 + \frac{1}{2}b_7 \text{Tr}[\vec{a}_0 \vec{a}_0] \omega^\mu \omega_\mu + b_8 \text{Tr}[\vec{a}_0 \vec{\rho}^\mu] \omega_\mu \sigma \end{aligned}$$

$$\mathcal{L}_I = \bar{\Psi}(-g_\sigma \sigma - g_\omega \gamma^\mu \omega_\mu - g_\rho \gamma^\mu \vec{\rho}_\mu - g_{a_0} \vec{a}_0)\Psi$$

$$\Psi = \begin{pmatrix} p \\ n \end{pmatrix}, \quad \vec{\rho}^\mu = \rho_i^\mu \tau_i, \quad \vec{a}^\mu = a_i^\mu \tau_i, \quad \Omega^{\mu\nu} = \partial^\mu \omega^\nu - \partial^\nu \omega^\mu, \quad P^{\mu\nu} = \partial^\mu \vec{\rho}^\nu - \partial^\nu \vec{\rho}^\mu$$

Preliminary results



AI For Physics

Parameter analysis for model
with 23 parameters

23 Par Esti

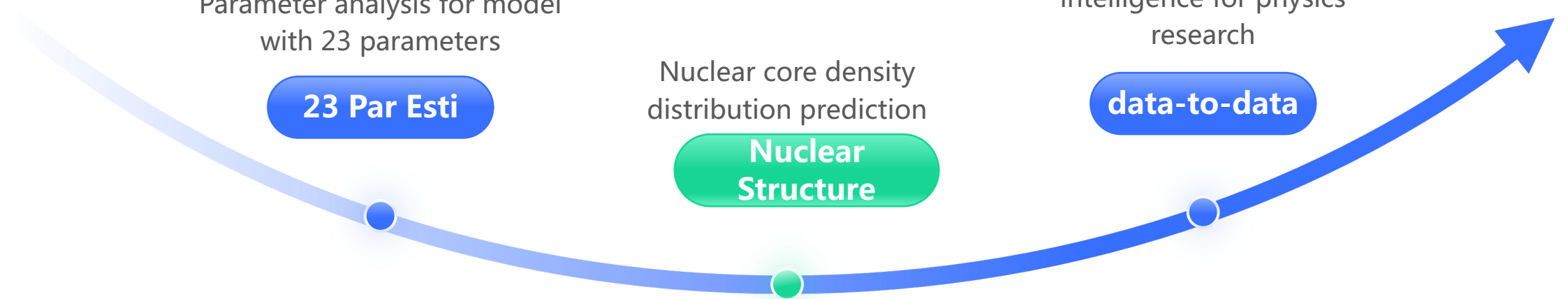
Nuclear core density
distribution prediction

**Nuclear
Structure**

Data-to-data level artificial
intelligence for physics
research

data-to-data

Outlook





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Thank you

