Inference of the neutron star matter equation of state

Condensed Matter Physics of QCD

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Neutron stars



- Masses $M \sim 1 2M_{\odot}$, radii $R \sim 11 13$ km
 - → High baryon densities in core beyond terrestrial experiments
- Recent substantial extension of observational data base
 - \rightarrow **Phase transition** in dense neutron star matter?

Equation of state

Internal structure described by Tolman-Oppenheimer-Volkoff (TOV) equations

S [Tolman, Phys. Rev. 55 (1939)] [Oppenheimer and Volkoff, Phys. Rev. 55 (1939)]

- ► Solved given equation of state (EoS) $P(\varepsilon)$ and central energy density $\varepsilon(r = 0) = \varepsilon_c$
 - \rightarrow Solution for different ε_c yields (*M*, *R*)-relation
- Each EoS has maximum density $\varepsilon_{c,\max}$ corresponding to maximum supported mass M_{\max}
- Simultaneously solve for tidal deformability Λ

[Flanagan and Hinderer, Phys. Rev. D 77 (2008)]



Speed of sound

Determine EoS from speed of sound

$$c_s^2(\varepsilon) = \frac{\partial P(\varepsilon)}{\partial \varepsilon}$$

- Causality & thermodynamic stability: $0 \le c_s \le 1$
- Characteristic signature of phase structure:
 - Nucleonic: monotonically rising sound speed
 - First-order phase transition: coexistence interval with zero sound speed c_s² ~ 0
 - Crossover: peaked behaviour

[McLerran and Reddy, Phys. Rev. Lett. 122 (2019)]

 Introduce general parametrization c²_s(ε,θ) to model diverse scenarios [Annala *et al.*, Nature Phys. 16, 907 (2020)]





Bayesian inference

• Constrain parameters of $c_s^2(\varepsilon, \theta)$ via **Bayesian inference** based on data \mathscr{D}

 $p(\theta|\mathcal{D}) \propto p(\mathcal{D}|\theta) p(\theta)$

- Compute posterior probability $p(\theta|\mathcal{D})$ for parameters θ :
 - Compute likelihood $p(\mathcal{D}|\theta)$ for each data \mathcal{D}
 - Choose prior for parameters $p(\theta)$
- ► Quantify evidence for hypothesis H₀ vs. H₁ with **Bayes factors**

$$\mathscr{B}_{H_0}^{H_1} = \frac{p(\mathscr{D}|H_1)}{p(\mathscr{D}|H_0)}$$

 \rightarrow Compare to classification scheme for statistical conclusions

[Lee and Wagenmakers, *Bayesian Cognitive Modeling* (Cambridge University Press, 2014)] [Jeffreys, *Theory of Probability* (Oxford University Press, 1961)]



[LB, Weise and Kaiser, Phys. Rev. D 108 (2023)]

Theory constraints

- Perturbative QCD calculations provide asymptotic boundary condition at n ≥ 40 n₀
 - \rightarrow Interpolate EoS at smaller densities with $0 \le c_s \le 1$

[Komoltsev and Kurkela, Phys. Rev. Lett. 128 (2022)]

Chiral effective field theory provides constraint at low densities

 \rightarrow Employ up to $n \le 1.3 n_0$

[Essick et al., Phys. Rev. C 102 (2020)]

Intermediate density regime unconstrained, use astrophysical data in addition



[[]Drischler, Han and Reddy, Phys. Rev. C 105 (2022)]

Astrophysical data

- Shapiro time delay: in binary systems gravitational field of companion changes pulsar signal
 - → Extract neutron star masses with high precision: [Antoniadis *et al.*, Science 340 (2013)] [Fonseca *et al.*, Astrophys. J. Lett. 915 (2021)] PSR J0348+0432 $M = 2.01 \pm 0.04 M_{\odot}$ PSR J0740+6620 $M = 2.08 \pm 0.07 M_{\odot}$
- **NICER:** hot spots on magnetic polar caps of neutron stars
 - \rightarrow Thermal X-ray emission modulated by gravitational field
- Infer mass and radius :

PSR J0030+0451 $R = 12.71^{+1.14}_{-1.19}$ km $M = 1.34^{+0.15}_{-0.16} M_{\odot}$ [Riley et al., Astrophys. J. Lett. 887 (2019)]PSR J0740+6620 $R = 12.39^{+1.30}_{-0.98}$ km $M = 2.072^{+0.067}_{-0.066} M_{\odot}$ [Riley et al., Astrophys. J. Lett. 918 (2021)]





Astrophysical data

- Binary neutron star mergers produce gravitational waves
- Waveform depends on M₂/M₁ and combination of tidal deformabilities

 $\begin{array}{ll} \mbox{GW170817} & \Bar{\Lambda} = 320^{+420}_{-230} \\ \mbox{GW190425} & \Bar{\Lambda} \leq 600 \end{array}$

of
$$\bar{\Lambda} = \frac{16}{13} \frac{(M_1 + 12M_2)M_1^4 \Lambda_1 + (M_2 + 12M_1)M_2^4 \Lambda_2}{(M_1 + M_2)^5}$$

[Abbott et al. (LIGO and Virgo Collaborations), Phys. Rev. X 9 (2019)]

[Abbott et al. (LIGO and Virgo Collaborations), Astrophys. J. Lett. 892 (2020)]

- Black widow pulsars accrete most of mass from companion
- ► PSR J0952-0607 heaviest neutron star observed so far

 $M = 2.35 \pm 0.17 M_{\odot}$

[Romani et al., ApJL 934 (2022)]

Second fastest known pulsar T = 1.41 ms, rotation correction via empirical formula

[Konstantinou and Morsink, Astrophys. J. 934, 139 (2022)]



Posterior results

- Steep increase of speed of sound around ε ~ 250 − 600 MeV fm⁻³ [LB. Weise and Kaiser, Phys. Rev. D 108 (2023)]
- Conformal bound $c_s^2 \le 1/3$ exceeded inside neutron stars

[Altiparmak, Ecker and Rezzolla, Astrophys. J. Lett. 939 (2022)] [Legred, Chatziioannou, Essick, Han and Landry, Phys. Rev. D 104 (2021)]

► Slight **tension** between ChEFT at $n \simeq 2 n_0$ and astro data

[Essick et al., Phys. Rev. C 102 (2020)]

- ► Median with almost constant radius *R* ~ 12.3 km
- ► Good agreement with data **not included** in Bayesian analysis:
 - Thermonuclear burster 4U 1702-429

[Nättilä et al., Astron. & Astrophys. 608 (2017)]

• $R(M = 1.4 M_{\odot})$ from quiescent low mass X-ray binaries (qLMXBs)







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Maximum coexistence interval

- Significantly increased pressure compared to previous EoS
- Maxwell construction of first-order phase transition: constant pressure in phase coexistence region
 - \rightarrow Width Δn measure of phase transition 'strength'
- Maximum possible interval within posterior credible band

 $\left(\frac{\Delta n}{n}\right)_{\max} \le 0.2$ at 68% level

[LB, Weise and Kaiser, Phys. Rev. D 108 (2023)]

Compare to 'strong' nuclear liquid-gas phase transition

 $\frac{\Delta n}{n} > 1$ [Fiorilla, Kaiser and Weise, Nucl. Phys. A 880 (2012)]

 \rightarrow Only weak first-order phase transitions <code>possible</code>



Evidence against small sound speeds

- Quantify evidence of small sound speeds inside neutron star cores with Bayes factor
- 10^{3} Previous $\mathscr{B}_{c_{s,\min}^2 \le 0.1}^{c_{s,\min}^2 \ge 0.1}$ Previous + BWextreme evidence 10^{2} $\rightarrow c_{s \min}^2 \leq 0.1$ prerequisite for first-order phase transition very strong **Bayes** factor • Previous analyses: $c_s^2 > 0.1$ in neutron stars with $M \le 2M_{\odot}$ strong [Ecker and Rezzolla, Astrophys. J. Lett. 939 (2022)] 10 [Annala et al., Nat. Commun. 14 (2023)] moderate Heavy mass measurement increases Bayes factor anecdotal 10° • Strong evidence against $c_{s \min}^2 \le 0.1$ in cores of neutron stars no evidence with $M \leq 2.1 M_{\odot}$ [LB. Weise and Kaiser, Phys. Rev. D 108 (2023)] 2.0 2.1 2.2 2.3 1.9 M/M_{\odot} -> Strong first-order phase transitions unlikely based on empirical data

Low-energy nucleon structure

• Central densities in neutron stars (68%):

 $n_c(1.4 M_{\odot}) = (2.6 \pm 0.4) n_0$ $n_c(2.3 M_{\odot}) = (3.8 \pm 0.8) n_0$

 \rightarrow Average distance between baryons d > 1 fm

- Two scales in nucleons:
 - Compact hard core contains valence quarks
- $R_{\rm core} \sim 1/2 \,{\rm fm}$
- Surrounding soft quark-antiquark cloud R_{cloud} ~ 1 fm
 [Fukushima, Koio and Weise, Phys. Rev. D 102 (2020)]
- At $n > 2 n_0$ percolation of quark-antiquark pairs
 - \rightarrow Cores begin to touch and overlap at $n > 5 n_0$



[[]LB and Weise, Symmetry 16 (2024)]

Chiral symmetry restoration

► Chiral nucleon-meson model: nucleons interacting via exchange of effective mesons

[Floerchinger and Wetterich, Nucl. Phys. A 890-891 (2012)]

- ► Mean-field (MF): first-order order phase transition to chirally restored phase
- Extended mean-field (EMF): fermionic vacuum fluctuations stabilize order parameter

[Skokov et al., Phys. Rev. D 82 (2010)]

- Functional renormalization group (FRG): further stabilization through additional pion and nucleon loops [Drews and Weise, Prog. Part, Nucl. Phys. 93 (2017)]
 - \rightarrow Comparable impact of fluctuations in alternative chiral models

[Gupta and Tiwari, Phys. Rev. D 85 (2012)] [Zacci and Schaffner-Bielich, Phys. Rev. D 97 (2018)]



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Neural likelihood estimation

- qLMXBs: X-ray spectra s in telescopes depend on (M, R) and nuisance parameters $v = (N_H, d, \log T_{eff})$
- Likelihood $p(s|\theta, v)$ analytically intractable
 - \rightarrow **Two steps:** infer neutron star mass and radius and use (*M*, *R*) posteriors as likelihood

[Riley, Raaijmakers and Watts, MNRAS 478 (2018)]

• Neural likelihood estimation: train neural network to approximate likelihood based on simulations

 $q_{\Phi}(\boldsymbol{s}|\boldsymbol{\theta},\boldsymbol{v})\approx p(\boldsymbol{s}|\boldsymbol{\theta},\boldsymbol{v})$

[Papamakarios, Sterratt and Murray, AISTAT (2019)]



Posterior results

- Spectral EoS model with only two parameters $\theta = (\lambda_1, \lambda_2)$
- Simulate telescope spectra with XSPEC

[Arnaud, ASP Conf. Ser. 17 (1996)]

- Likelihood differentiable → can use Hamiltonian Monte Carlo sampling
- ► Full posterior p(θ, v|s) directly from (simulated) telescope spectra
 - → Spectrum can contain additional EoS information not captured by (*M*, *R*) [Elshamouty *et al.*, Astrophys. J. 826 (2016)]
- On simulated test data surpass accuracy of all previous methods [Farrell et al., JCAP 02 (2023)] [Farrell et al., JCAP 12 (2023)]





[LB et al., arXiv:2403.00287 (2024)]

Scaling to more observations

- Amortization: need to train neural network only once
 - \rightarrow Inexpensive likelihood evaluation
 - \rightarrow Inclusion of additional observations straightforward
 - \rightarrow Expect many more measurements in the future
- Future: apply to real telescope spectra
- Extend approach to NICER or GW data



Summary

- Bayesian inference of sound speed in neutron star matter based on theory constraints and astro data
- Maximum possible phase coexistence interval $(\Delta n/n)_{\text{max}} \le 0.2$
- ► Strong evidence against $c_{s,\min}^2 \le 0.1$ in cores of neutron stars with $M \le 2.1 M_{\odot}$

\rightarrow Strong first-order phase transitions unlikely based on empirical data

- Central densities $n_c < 5 n_0$ for $M \le 2.3 M_{\odot}$: average distance between baryons still > 1 fm
 - \rightarrow Fluctuations stabilize hadronic phase?
- Full posterior directly from telescope spectra with neural likelihood estimation
 - \rightarrow Naturally scales to growing number of observations expected in coming years

Supplementary material

Outlook

- Fourth observation run of LIGO, Virgo and KAGRA started on May 4th
- ► Four more objects to be measured by NICER telescope
- Moment-of-inertia measurement of PSR J0737-3039 in next few years
- Extract more information with novel statistical tools from Machine Learning

[LB et al., arXiv:2403.00287 (2024)]

[Landry and Kumar, Astrophys. J. 868 (2018)]

[Greif et al., MNRAS 485 (2019)]

→ Many more future measurements will put even tighter constraints on phase structure at high densities

nature	
The golden age of neutron-star physics has arrived	
These stellar remnants are some of the Universe's most enigmatic objects – and they are inally starting to give up their secrets.	
Adam Mann	

Chiral nucleon-meson model

• Interactions of fermions via the exchange of effective mesons: Nambu-Goldstone boson π and heavy σ

 \rightarrow Short distance dynamics modelled by massive vector fields

[Floerchinger and Wetterich, Nucl. Phys. A 890-891 (2012)]

► Boson self-interactions and explicit symmetry breaking term

$$\mathscr{U}(\sigma, \pi) = (\pi, \sigma) + \cdots + m_{\pi}^{2} t_{\pi} (\sigma - t_{\pi})$$

- Expectation value $\langle \sigma \rangle$ dynamically creates nucleon mass

 $\rightarrow \langle \sigma \rangle / \langle \sigma \rangle_{vac} = \langle \sigma \rangle / f_{\pi}$ order parameter for chiral symmetry

Mass-radius data

- Mass-radius data of neutron stars:
 - Pulse profile modelling [Riley et al., Astrophys. J. Lett. 887 (2019)]
 - Thermonuclear bursters [Nättilä *et al.*, Astron. & Astrophys. 608 (2017)]
 - Quiescent low mass X-ray binaries

[Steiner et al., Mon. Not. Roy. Astron. Soc. 476 (2018)]

- Measurements of X-ray spectra in telescopes
 - → Depends on (*M*, *R*) and **nuisance parameters** $v = (N_H, d, \log T_{eff})$
 - \rightarrow Information from other observations $\tilde{p}(\nu)$
- Infer neutron star mass and radius using e.g. XSPEC package [Arnaud, Jacoby and Barnes, ASP Conf. Series volume 101 (1996)]
- ► Use (*M*, *R*) **posteriors as likelihood**, valid for flat priors

 $p(\mathcal{D}|M,R) \propto p(M,R|\mathcal{D})$



Mass-radius data

- Complicated (M, R) posterior distributions available via samples
 - \rightarrow Approximate with Kernel Density Estimation (KDE)

$$\hat{f}_h(x) = \frac{1}{Nh} \sum_{i=1}^N K\left(\frac{x - x_i}{h}\right) \qquad K(z) = \frac{1}{\sqrt{2\pi}} \exp\left(-\frac{z^2}{2}\right)$$

- \rightarrow Depends on bandwidth parameter h
- Solve TOV equations to obtain $R(M, \lambda)$
- Likelihood:

 $p(M, R|\mathscr{D}) = \int_{M}^{M_{\max}(\lambda)} dM \ \mathsf{KDE}(M, R(M, \lambda)) p(M)$ [LB, Weise and Kaiser, Phys. Rev. D 108 (2023)]

• Mass prior p(M) of neutron star mass population



Implicit assumptions

- · Only few measurements available so far
 - \rightarrow Large uncertainties, results prior dependent
- Results depend on implicit assumptions:
 - Bandwidth of KDE

▶ ...

- Posteriors as likelihood
- Unknown neuron star mass population
- Modelling of neutron star atmospheres

→ Complimentary **Machine Learning** analysis





Neural Likelihood Estimation

• Train neural density estimator (normalizing flow) to approximate likelihood based on telescope spectra s

 $q_{\phi}(s|\lambda, v) \approx p(s|\lambda, v)$

[Papamakarios, Sterratt and Murray, AISTAT (2019)]

• Sample (λ_i, v_i, s_i) from $p(\lambda, v, s)$

$$\begin{split} \lambda_i &\sim p(\lambda) \\ \nu_i &\sim p(\nu) \\ s_i &\sim p(s|\lambda_i, \nu_i) \quad \text{via simulator based on XSPEC plus noise} \end{split}$$

• **Training** q_{ϕ} based on (λ_i, v_i, s_i) equals maximizing $\sum_i \log q_{\phi}(s_i | \lambda_i, v_i)$

$$\mathbb{E}_{p(\lambda,\nu,s)}\left[\log q_{\phi}(s|\lambda,\nu)\right] = -\mathbb{E}_{p(\lambda,\nu)}\left[D_{KL}\left(p(s|\lambda,\nu)\middle|\left|q_{\phi}(s|\lambda,\nu)\right)\right] + \text{const}\right]$$

- \rightarrow Kullback-Leibler divergence zero for $q_{\phi}(s|\lambda, v) = p(s|\lambda, v)$
- ► Insert real telescope spectrum s₀

 $p(s_0|\lambda, v) \approx q_{\phi}(s_0|\lambda, v)$

Neural Likelihood Estimation

Multiply with priors and sample from posterior

 $p(\lambda, v|s_0) \propto q_{\phi}(s_0|\lambda, v_0) \tilde{p}(v_0) p(v) p(\lambda)$

→ Different scenarios for prior information on nuisance parameters $\tilde{p}(v_0)$ (true, tight, loose)

parameter	true	tight	loose
d	exact	5%	20%
N _H	exact	30%	50%
$\log(T_{eff})$	exact	±0.1	±0.2

- ► Can use Hamiltonian Monte Carlo (HMC) for sampling
- Normalizing flows: distribution *p*(*x*) via *invertible and differentiable* transformations *f*_{θi} of base distribution *π*(*u*)

 \rightarrow Compute probability density and generate samples

- Here: distribution of spectra s conditioned on λ and v



NLE for neutron stars

1. Train 100 neural density estimators with (s, λ, v) with different hyperparameters

 \rightarrow Use only top 5 $\bar{q}_{\phi}(s|\lambda, v) = \frac{1}{N} \sum_{j} q_{\phi_{j}}(s|\lambda, v)$

- 2. Here: combine likelihoods for 10 simulated test spectra
- 3. Multiply with priors $p(\lambda)$, p(v) and nuisance parameter information $\tilde{p}(v_i)$
- 4. Sample from posterior using HMC $p(\lambda, v|s) \propto \left(\prod_i \bar{q}_{\phi}(s_i|\lambda, v_i)\tilde{p}(v_i)\right) p(\lambda) p(v)$



Posterior distribution

- Posterior directly from telescope spectra
 - \rightarrow Here based on 10 simulated spectra for one example EoS
- Three scenarios: true (green), tight (orange) and loose (blue)
 - \rightarrow Uncertainties much smaller in true case
- Constrain N_H and log T_{eff} much better than prior information
 - \rightarrow In tight case *d* posterior similar to prior
- Transform into $P(\varepsilon)$ and R(M) constraints



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Posterior distribution

- Posterior directly from telescope spectra
 - \rightarrow Uncertainty propagated via normalizing flow
- Possible to combine with likelihoods from other data (e.g. gravitational waves)
- Amortization: need to train the density estimator only once
 - → Faster likelihood computation
 - → Easy to include new measurements, analyse impact of future measurements
- Expected to extend easily to more complex EoS model



Performance

- Compute **maximum posterior estimate** ($\lambda_{1,pred}, \lambda_{2,pred}$) for 100 random EoS
 - \rightarrow Again 10 simulated spectra for each EoS
- Compare to ground truth values $(\lambda_{1,true}, \lambda_{2,true})$
 - \rightarrow Distribution centered around 0, **no systematic bias**



Performance

Compare mean and standard deviation to previous approaches

$$\sigma_{tot} = \sqrt{\sigma_{\lambda_1}^2 + \sigma_{\lambda_2}^2}$$

→ Better performance than previous approaches!

[Farrell et al., JCAP 02 (2023)] [Farrell et al., JCAP 12 (2023)]



Work in progress

- Sample spectra from likelihood and compare to simulations for given λ and ν
 - \rightarrow Need to marginalize over mass and radius (left)
- Large differences, use mass as additional nuisance parameter?
 - \rightarrow Much better agreement (right), can infer mass and radius of NS from spectra
- ► But: parameter space increases, multimodal distributions, sampling problems



Nucleon radii

Axial radius from neutrino-deuteron scattering

 $\langle r_A^2 \rangle = (0.46 \pm 0.22) \, \mathrm{fm}^2$

[Hill et al., Rep. Prog. Phys. 81 (2018)]

 \rightarrow Subtract dominant cloud contribution from a_1 meson

$$\sqrt{\langle r_A^2 \rangle}_{\text{core}} = \left[\langle r_A^2 \rangle - \delta \langle r_A^2 \rangle \right]^{1/2} \simeq 0.55 \,\text{fm}$$

• Mass radius of proton from J/Ψ photoproduction (\rightarrow dominated by gluon dynamics at nucleon center)

$$\sqrt{\langle r^2 \rangle_{\text{mass}}} = (0.55 \pm 0.03) \,\text{fm}$$

[Kharzeev, Phys. Rev. D 104 (2021)]

Baryonic core radius from isoscalar and isovector radii

 $\sqrt{\langle r_B^2 \rangle} \simeq 0.47 \,\mathrm{fm}$

► Cloud range given e.g. by proton charge radius

 $\sqrt{\langle r_p^2 \rangle} = (0.840 \pm 0.003) \, \text{fm}$

[Lin, Hammer and Meißner, Phys. Rev. Lett. 128 (2022)]

Twin stars

- Strong phase transitions can lead to mass-radius relations with multiple stable branches ('twin stars')
- Bayes factor gives extreme evidence against multiple stable branches [Gorda et al., arXiv:2212.10576 (2022)]
- ► Without likelihood from ChEFT 'only' strong evidence:

 $\mathscr{B}_{N_{\text{branches}} > 1}^{N_{\text{branches}} = 1} = 12.97$

[Essick, Legred, Chatziioannou, Han and Landry, arXiv:2305.07411 (2023)]

• Disconnection takes place at $M \sim 0.8 M_{\odot}$

 \rightarrow Unlikely based on nuclear phenomenology



Possible impact of HESS J1731-347

Central compact object within supernova remnant HESS J1731-347:

 $M = 0.77^{+0.20}_{-0.17} M_{\odot}$ $R = 10.4^{+0.86}_{-0.78}$ km

[Doroshenko et al., Nat. Astron. 6 (2022)]

- Unusually light neutron star with very low radius
 - \rightarrow Neutron star mass $M < 1.17 M_{\odot}$ in contradiction with known formation mechanisms [Suwa et al., MNRAS 481 (2018)]

 \rightarrow Strange star?

Systematic uncertainty: larger masses and radii might be possible

[Alford and Halpern, Astrophys, J. 944 (2023)]

Tension between HESS and current astrophysical data

[Jiang, Ecker and Rezzolla, arXiv:2211.00018 (2022)]





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General EoS parametrization

Determine EoS from speed of sound

$$c_s^2(\varepsilon) = \frac{\partial P(\varepsilon)}{\partial \varepsilon}$$

Parametrize by segment-wise linear interpolations

$$C_{s}^{2}(\varepsilon,\theta) = \frac{(\varepsilon_{i+1} - \varepsilon)C_{s,i}^{2} + (\varepsilon - \varepsilon_{i})C_{s,i+1}^{2}}{\varepsilon_{i+1} - \varepsilon_{i}}$$
[Annala *et al.*, Nature Phys. 16, 907 (2020)]

- Matching to BPS crust at low densities $(c_{s,0}^2, \varepsilon_0) = (c_{s,crust}^2, \varepsilon_{crust})$ [G. Baym, C. Pethick, and P. Sutherland, Astrophys. J. 170 (1971)]
- ► Constant speed of sound $c_s^2(\varepsilon, \theta) = c_{s,N}^2$ beyond last point $\varepsilon > \varepsilon_N$
- Choose N = 5 corresponding to 7 segments and 10 free parameters
- Priors sampled logarithmically

$$c_{s,i}^2 \in [0,1]$$
 $\varepsilon_i \in [\varepsilon_{crust}, 4 \,\mathrm{GeV}\,\mathrm{fm}^{-3}]$

Parametrizations with only 4 segments leads to comparable results as non-parametric Gaussian process

[Annala et al., arXiv:2303.11356 (2023)]

Bayesian inference

► Bayes theorem:

$$p(\theta|\mathcal{D},\mathcal{M}) = \frac{p(\mathcal{D}|\theta,\mathcal{M})p(\theta|\mathcal{M})}{p(\mathcal{D}|\mathcal{M})}$$

- Choose **Priors** for parameters $p(\theta|\mathcal{M})$
- ► Likelihood $p(\mathscr{D}|\theta, \mathscr{M})$: probability of data \mathscr{D} to occur for θ and model \mathscr{M}
- (M, R, Λ) can be deterministically determined for θ

 $p(\mathcal{D}|\theta,\mathcal{M}) = p(\mathcal{D}|M,R,\Lambda,\mathcal{M})$

→ For computational feasibility assume (valid for flat Priors in (M, R, Λ)) $p(\mathscr{D}|M, R, \Lambda, \mathscr{M}) \propto p(M, R, \Lambda | \mathscr{D}, \mathscr{M})$

[Riley, Raaijmakers and Watts, Mon. Not. Roy. Astron. Soc. 478 (2018)] [Raaijmakers et al., ApJL 918 (2021)]

Bayesian inference

Bayes theorem:

$$p(\theta|\mathcal{D},\mathcal{M}) = \frac{p(\mathcal{D}|\theta,\mathcal{M})p(\theta|\mathcal{M})}{p(\mathcal{D}|\mathcal{M})}$$

• Evidence $p(\mathcal{D}|\mathcal{M})$: determined via normalization of the posterior

$$p(\mathcal{D}|\mathcal{M}) = \int d\theta \ p(\mathcal{D}|\theta, \mathcal{M}) p(\theta|\mathcal{M})$$

- \rightarrow High-dimensional integral, use sampling techniques
- Credible bands: determine $P(\varepsilon_i, \theta)$ on grid $\{\varepsilon_i\}$ for posterior samples to get $p(P|\varepsilon_i, \mathcal{D}, \mathcal{M})$

 \rightarrow Compute credible interval [*a*,*b*] with probability α at ε_i

$$\alpha = \int_{a}^{b} dP \ p(P|\varepsilon_{i},\mathcal{D},\mathcal{M})$$

 \rightarrow Combine credible intervals at all ε_i to posterior credible band $P(\varepsilon)$

Trace anomaly measure

Trace anomaly measure as signature of conformality

$$\Delta = \frac{g_{\mu\nu}T^{\mu\nu}}{3\varepsilon} = \frac{1}{3} - \frac{P}{\varepsilon}$$

[Fujimoto, Fukushima, McLerran and Praszałowicz, Phys. Rev. Lett. 129 (2022)]

- Median becomes negative around $\varepsilon \sim 700 \,\mathrm{MeV \, fm^{-3}}$
 - \rightarrow Moderate evidence for Δ turning **negative** inside neutron stars

Bayes factor $\mathscr{B}_{\Delta\geq 0}^{\Delta<0} = 8.11$

[Ecker and Rezzolla, Astrophys. J. Lett. 939 (2022)] [Annala *et al.*, arXiv:2303.11356 (2023)] [Marczenko, McLerran, Redlich and Sasaki, Phys. Rev. C 107 (2023)]

► At higher energy densities again positive ∆ to reach asymptotic pQCD limit



Chiral effective field theory

- ► Previous analyses: only EoS within ChEFT band a priori
- ChEFT uncertainties represent variety of empirical nuclear data
 - → Similar treatment to astro data allows balancing between constraints and consistent Bayes factor analysis
- Likelihood via Bayesian linear regression:

$$p(\mathscr{D}_{\mathsf{ChEFT}} | c_s^2(n,\theta)) \\ \propto \exp\left[-\frac{1}{2} \int_{0.5 \, n_0}^{n_{\mathsf{ChEFT}}=1.3 \, n_0} \mathrm{d}n \, \left(\frac{\langle c_s^2(n) \rangle - c_s^2(n,\theta)}{\sigma(n)}\right)^2\right]$$



• Slight **tension** between ChEFT at $n \simeq 2n_0$ and astro data

[Essick et al., Phys. Rev. C 102 (2020)]

Impact of pQCD

• Matching to pQCD at $n_{c,max}$ has only **negligible impact**

[Somasundaram, Tews and Margueron, arXiv:2204.14039 (2022)]

- ► Change matching to asymptotic pQCD from *n_{c,max}* to 10 *n*₀
 - \rightarrow Much smaller c_s^2 at high energy densities

[Gorda, Komoltsev, and Kurkela, arXiv:2204.11877 (2022)] [Komoltsev and Kurkela, Phys. Rev. Lett. 128 (2022)]

- \rightarrow Few changes in mass-radius, properties of 2.3 M_{\odot} neutron star change only slightly
- EoS beyond $n_{c,max}$ no longer constrained by astrophysical data
 - → Impact depends unconstrained interpolation to high densities [Essick, Legred, Chatziioannou, Han and Landry, arXiv:2305.07411 (2023)]



Perturbative QCD

• Connection of $(\mu_{NS}, n_{NS}, P_{NS})(\theta)$ to $(\mu_{pQCD}, n_{pQCD}, P_{pQCD})$

$$\int_{\mu_{\rm NS}}^{\mu_{\rm pQCD}} d\mu \ n(\mu) = P_{\rm pQCD} - P_{\rm NS} = \Delta P$$

 Causality and thermodynamic stability imply minimum and maximum values

$$\Delta P_{\min} = \frac{\mu_{pQCD}^2 - \mu_{NS}^2}{2\mu_{NS}} n_{NS} \quad \Delta P_{\max} = \frac{\mu_{pQCD}^2 - \mu_{NS}^2}{2\mu_{pQCD}} n_{pQCD}$$

Likelihood

$$p(\mathcal{D}_{pQCD} | \Delta P(\theta), \mathcal{M}) = \begin{cases} 1 & \text{if } \Delta P(\theta) \in [\Delta P_{\min}(\theta), \Delta P_{\max}(\theta)] \\ 0 & \text{else} \end{cases}$$

→ Take logarithmic average over renormalisation scale $X \in [1/2, 2]$

[Komoltsev and Kurkela, Phys. Rev. Lett. 128 (2022)]



[Gorda, Komoltsev, and Kurkela, arXiv:2204.11877 (2022)]

Mean-field approximation

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• Mean-field (MF) approximation: replace chiral boson fields by expectation values $\langle \sigma \rangle$ and $\langle \pi \rangle = 0$

→ Diverging fermionic vacuum contribution:
$$\delta \Omega_{\text{vac}} = -4 \int \frac{d^3 p}{(2\pi)^3} E$$

- ► Compute with dimensional regularisation in extended mean-field (EMF) approach [Skokov et al., Phys. Rev. D 82 (2010)]
- ► Adjust model parameters to reproduce empirical nuclear properties, i.e., liquid-gas phase transition

[Elliot et al., Phys. Rev. C 87 (2013)]



[LB, Kaiser and Weise, Eur. Phys. J. A 57 (2021)]

Functional Renormalization Group

- Additional fluctuations beyond vacuum contribution (chiral boson and nucleon loops)
 - → Include using non-perturbative Functional Renormalization Group (FRG) approach

[Drews and Weise, Prog. Part. Nucl. Phys. 93 (2017)]

- Initialize scale-dependent effective action $\Gamma_k[\Phi]$ at $k_{UV} \sim 4\pi f_{\pi}$
- Evolution $k \rightarrow 0$ governed by Wetterich's flow equation

$$k\frac{\partial\Gamma_{k}[\Phi]}{\partial k} = \frac{1}{2}\operatorname{Tr}\left[k\frac{\partial R_{k}}{\partial k} \cdot \left(\Gamma_{k}^{(2)}[\Phi] + R_{k}\right)^{-1}\right]$$

[Wetterich, Phys. Lett. B 301 (1993)]

• $\Gamma_k[\Phi]$ contains all **fluctuations** with $p^2 \ge k^2$ through regulator $R_k(p)$



 $\Gamma_{k=0}[\Phi]=\Gamma[\Phi]$

Phase structure

- *Mean-field:* unphysical **first-order order phase transition** to chirally restored phase
- ► Extended mean-field: vacuum contribution stabilizes order parameter
- ► FRG: further stabilization through additional fluctuations
 - \rightarrow **Smooth crossover** at densities $n > 6 n_0$ (with $n_0 = 0.16 \text{ fm}^{-3}$)
 - \rightarrow No phase transition in neutron star matter?



Inference of the neutron star matter equation of state | Len Brandes

Likelihoods

- EoS supports masses between M_{\min} and $M_{\max}(\theta)$
- Choose flat **mass prior** and $M_{\rm min} = 0.5 M_{\odot}$

$$p(M(\theta)) = \begin{cases} \frac{1}{M_{\max}(\theta) - M_{\min}} & \text{if } M \in [M_{\min}, M_{\max}(\theta)] \\ 0 & \text{else} \end{cases}$$

[Landry, Essick and Chatziioannou, Phys. Rev D 101 (2020)]

- When number of data increases incorporate mass population
 - \rightarrow Wrong population model causes a bias

[Mandel, Farr and Gair, Mon. Not. Roy. Astron. Soc. 486 (2019)]

► Assume Shapiro mass measurements Gaussian to compute likelihood

$$p(M(\theta)|\mathscr{D}_{\text{Shapiro}},\mathscr{M}) = \int_{M_{\min}}^{M_{\max}(\theta)} dM \,\mathscr{N}(M, \langle M \rangle, \sigma_M) \, p(M(\theta))$$
$$\approx \frac{1}{2} \left[1 + \operatorname{erf}\left(\frac{M_{\max}(\theta) - \langle M \rangle}{\sqrt{2}\sigma_M}\right) \right] \, p(M(\theta))$$

Likelihoods

- ► Data available as samples, approximate underlying probability with Kernel Density Estimation (KDE)
- ► Solve TOV equations to obtain $R(M, \theta)$ and $\Lambda(M, \theta)$
- NICER likelihood:

$$p((M,R)(\theta)|\mathcal{D}_{\text{NICER}},\mathcal{M}) = \int_{M_{\min}}^{M_{\max}(\theta)} dM \text{ KDE}(M,R(M,\theta))p(M(\theta))$$

GW likelihood:

$$p((M,\Lambda)(\theta)|\mathscr{D}_{\mathsf{GW}},\mathscr{M}) = \int \mathrm{d}M_1 \int \mathrm{d}M_2 \; \mathsf{KDE}(M_1,M_2,\Lambda(M_1,\theta),\Lambda(M_2,\theta))$$

- Do not assume neutron star-neutron star merger events
 - \rightarrow GW likelihood not weighted by mass prior and $\Lambda(M) = 0$ for black holes
- Do not assumed fixed chirp mass $M_{\text{chirp}} = (M_1 M_2)^{3/5} (M_1 + M_2)^{-1/5}$

Conformal limit

- Derived from naive dimensional analysis and asymptotic limit

$$\mu \gg \Lambda_{\text{QCD}} \implies P \propto \mu^{d+1}$$
$$c_s^2 = \frac{\partial P}{\partial \varepsilon} \sim \frac{1}{d}$$

[Hippert, Fraga and Noronha, Phys. Rev. D 104 (2021)]

Expected to hold in all conformal field theories

[Bedaque and Steiner, Phys. Rev. Lett. 114 (2015)]

• Recent Bayesian analyses found speeds of sound $c_s^2 > 1/3$ inside neutron stars

[Landry, Essick and Chatziioannou, Phys. Rev. D 101 (2020)] [Gorda, Komoltsev, and Kurkela, arXiv:2204.11877 (2022)] [Altiparmak, Ecker, and Rezzolla, arXiv:2203.14974 (2022)] [Leonhardt *et al.*, Phys. Rev. Lett. 125 (2020)]

 \rightarrow Also $c_s^2 > 1/3$ in recent $N_C = 2$ **lattice QCD**

[lida and Itou, PTEP 2022 (2022)]

Hard Dense Loop resummation methods: conformal limit may be approached asymptotically from above

[Fujimoto and Fukushima, Phys. Rev. D 105 (2022)]

Parametrization dependence

- 'Old' segment-wise parametrisation: different ChEFT constraint, $c_s^2 = 1/3$ reached asymptotically from below
- Compared to skewed Gaussian plus logistic function to reach asymptotic limit $c_s^2 = 1/3$

$$c_{s}^{2}(x,\theta) = a_{1} \exp\left[-\frac{1}{2} \frac{(x-a_{2})^{2}}{a_{3}^{2}}\right] \left(1 + \exp\left[\frac{a_{6}}{\sqrt{2}} \frac{x-a_{2}}{a_{3}}\right]\right) + \frac{1/3 - a_{7}}{1 + \exp\left[-a_{5}(x-a_{4})\right]} + a_{7}$$

[Greif et al,, MNRAS 485, 5363 (2019)] [Tews, Margueron and Reddy, EPJA 55, 97 (2019)]

Very similar findings, results robust against change of parametrization and Prior

