How can deep learning help us decipher neutron star composition

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Young
Astronomers
Meet

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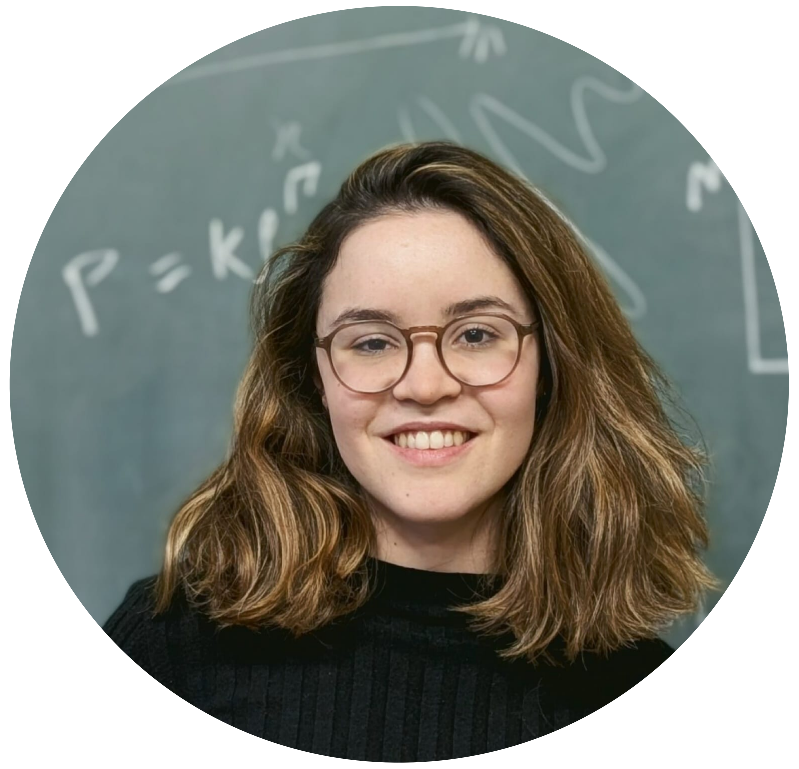

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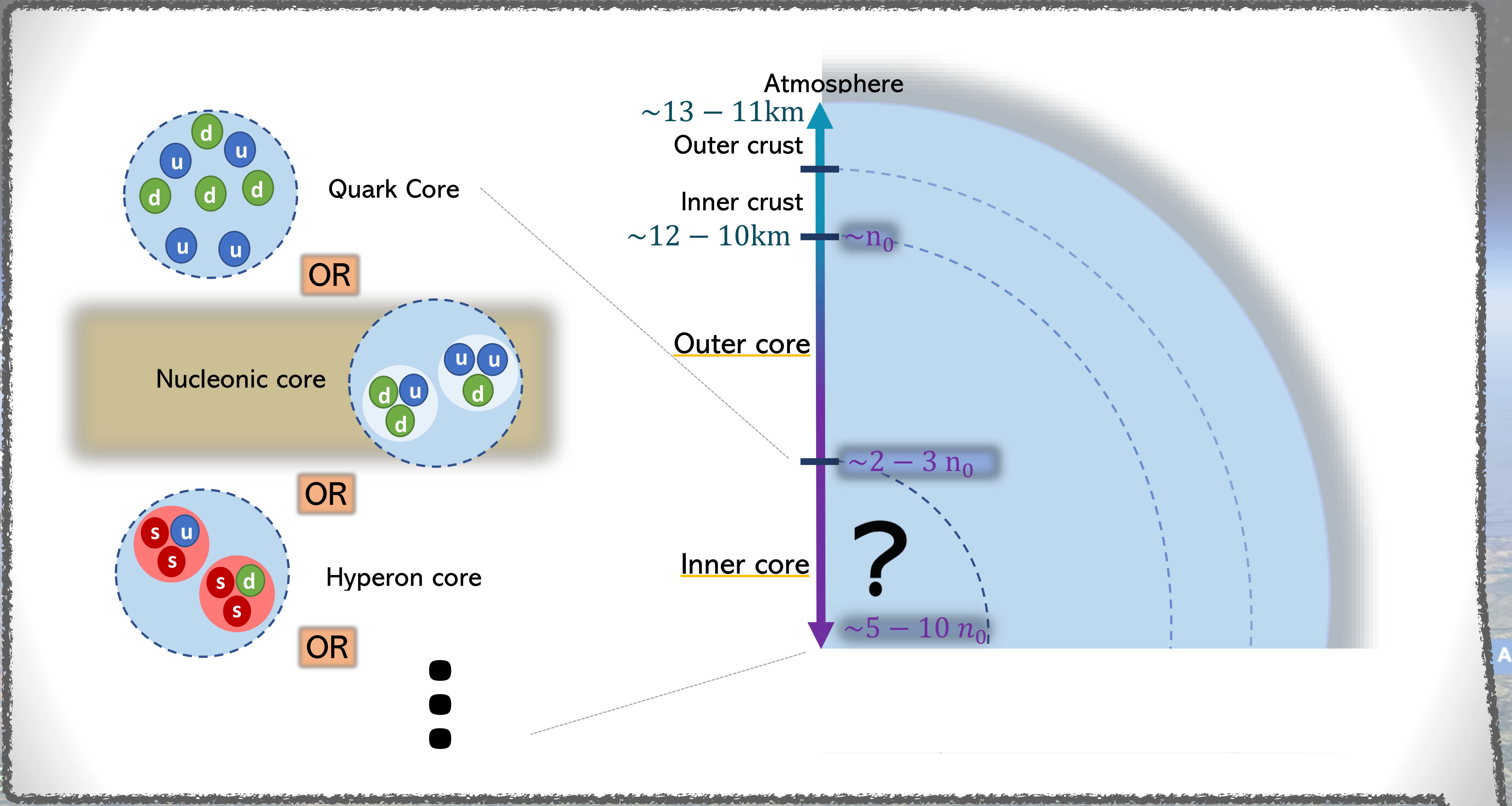
Outline

- **Motivation:**
  - What do we aim to study in neutron stars;
  - What is deep learning;
- **Example:**

How effectively can Neural Posterior Estimation infer the Neutron Star Equation of State

What's inside a neutron star?



$$M = 1 \sim 2M_\odot$$

$$R \approx 10^{-5}\, R_\odot$$

$$T=0$$

The equation of state: A bridge between micro and macro

Equation of State(EoS)

$$p(\varepsilon)$$

Speed of Sound

$$c_s^2(n) = \frac{dp(n)}{d\varepsilon(n)}$$

Trace Anomaly

$$\Delta(n) = \frac{1}{3} - \frac{p(n)}{\varepsilon(n)}$$

Tolman-Oppenheimer-Volkoff equations

$$\frac{dP(r)}{dr} = -\frac{\varepsilon(r)m(r)}{r^2}\left(1+\frac{P(r)}{\varepsilon(r)}\right)\left(1+\frac{4\pi r^3 P(r)}{m(r)}\right)\left(1-\frac{2m(r)}{r}\right)^{-1}$$

$$\frac{dm(r)}{dr} = 4\pi r^2 \varepsilon(r)$$

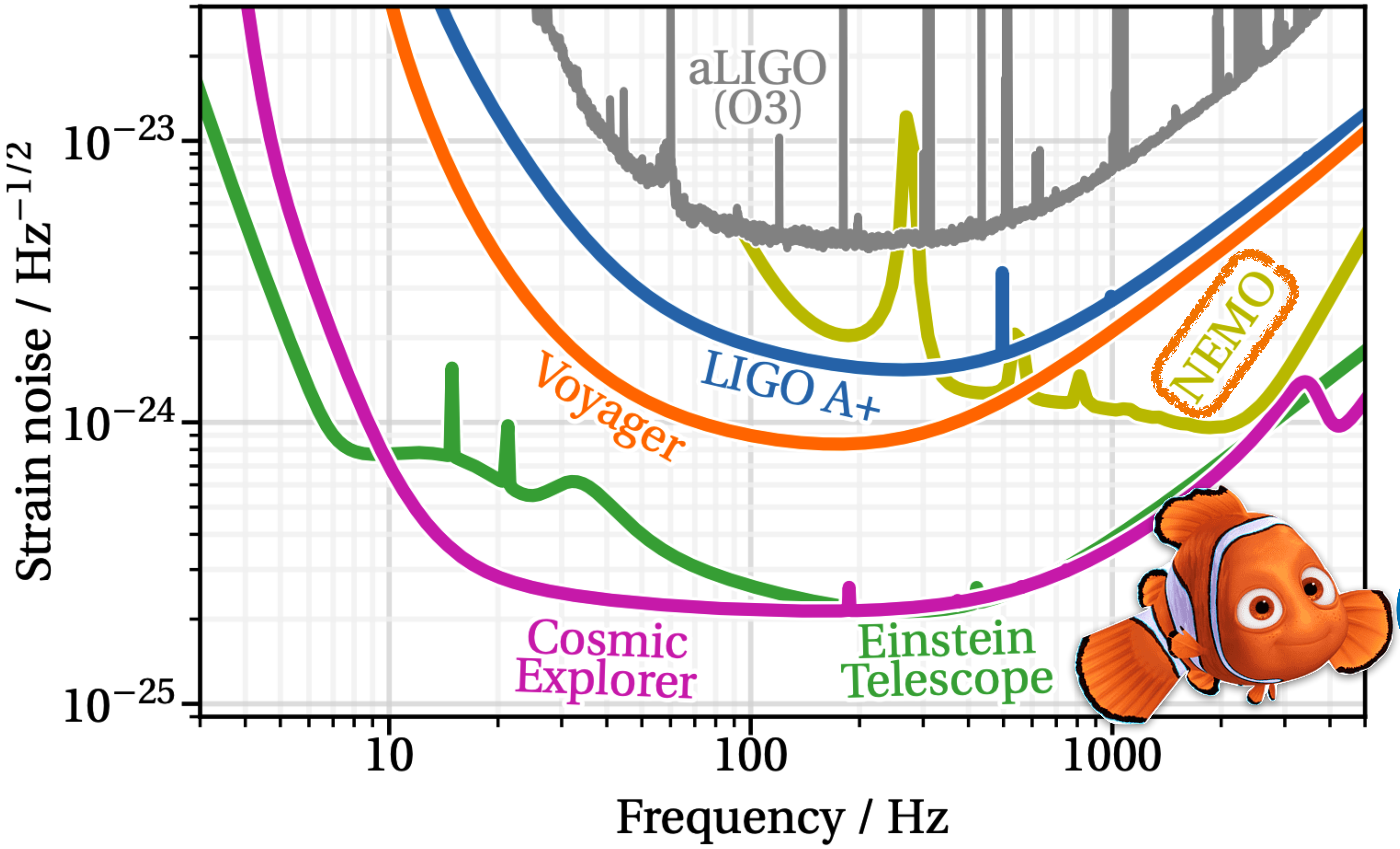
Tidal deformability

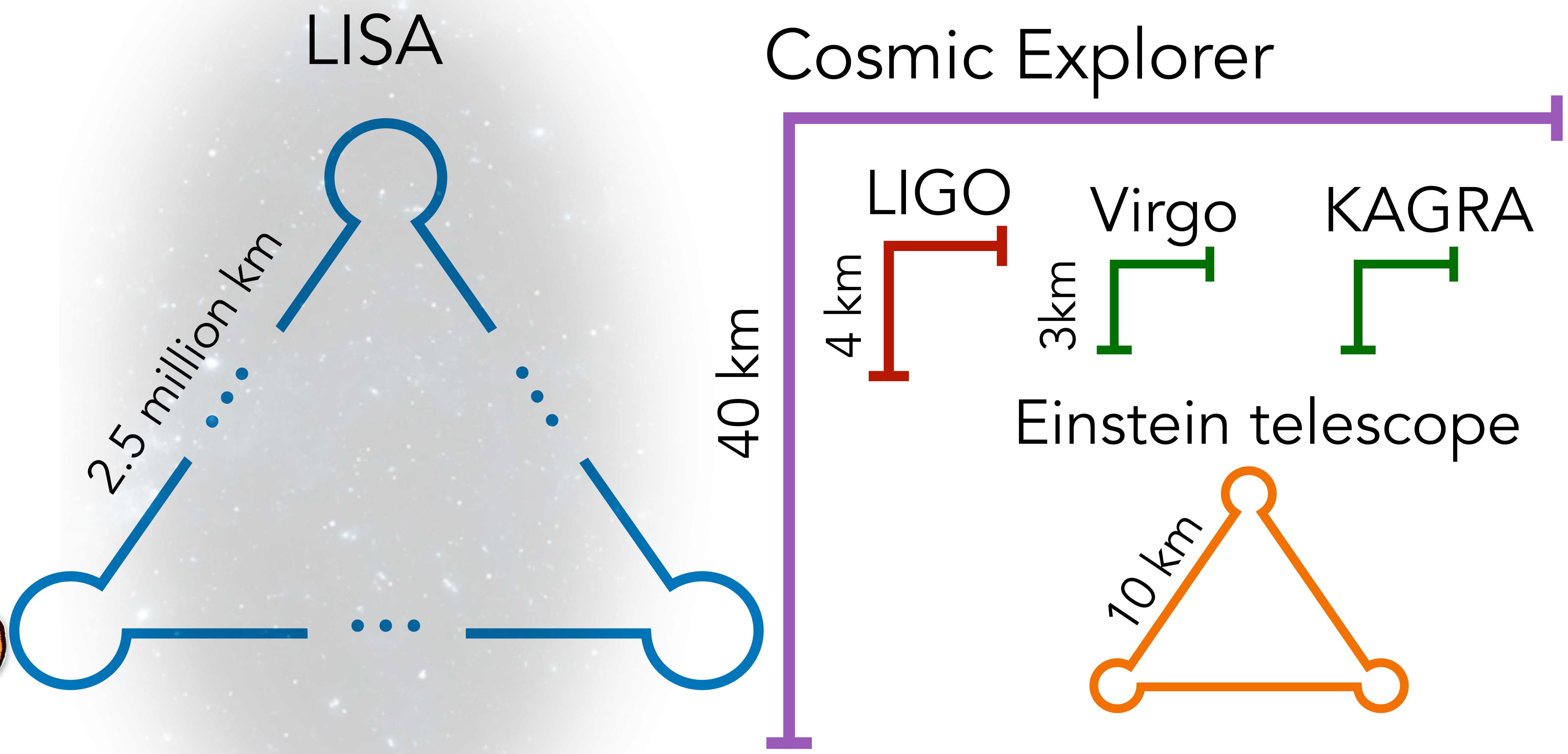
$$\Lambda = \frac{2}{3}k_2 C^{-5}, \qquad C = \frac{M}{R}$$

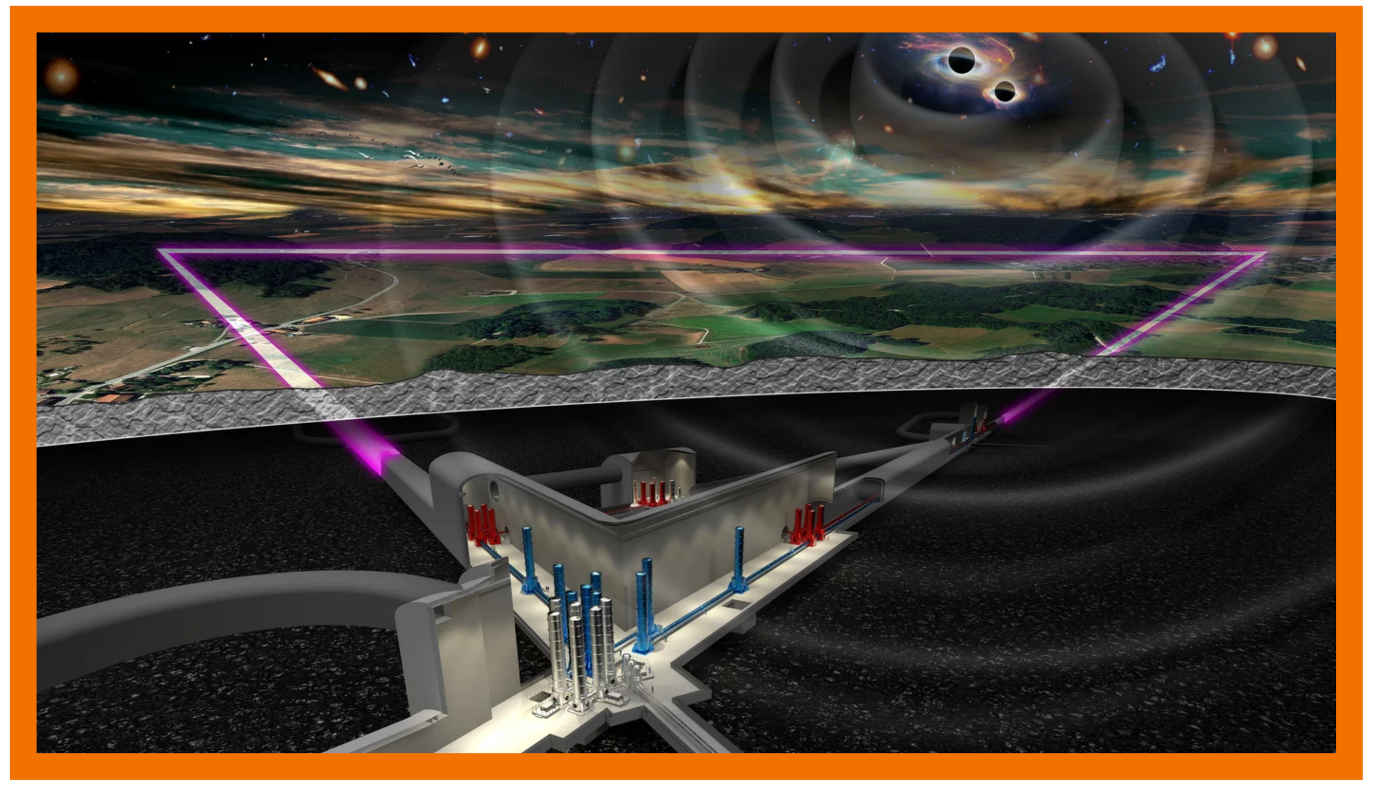
Current observations

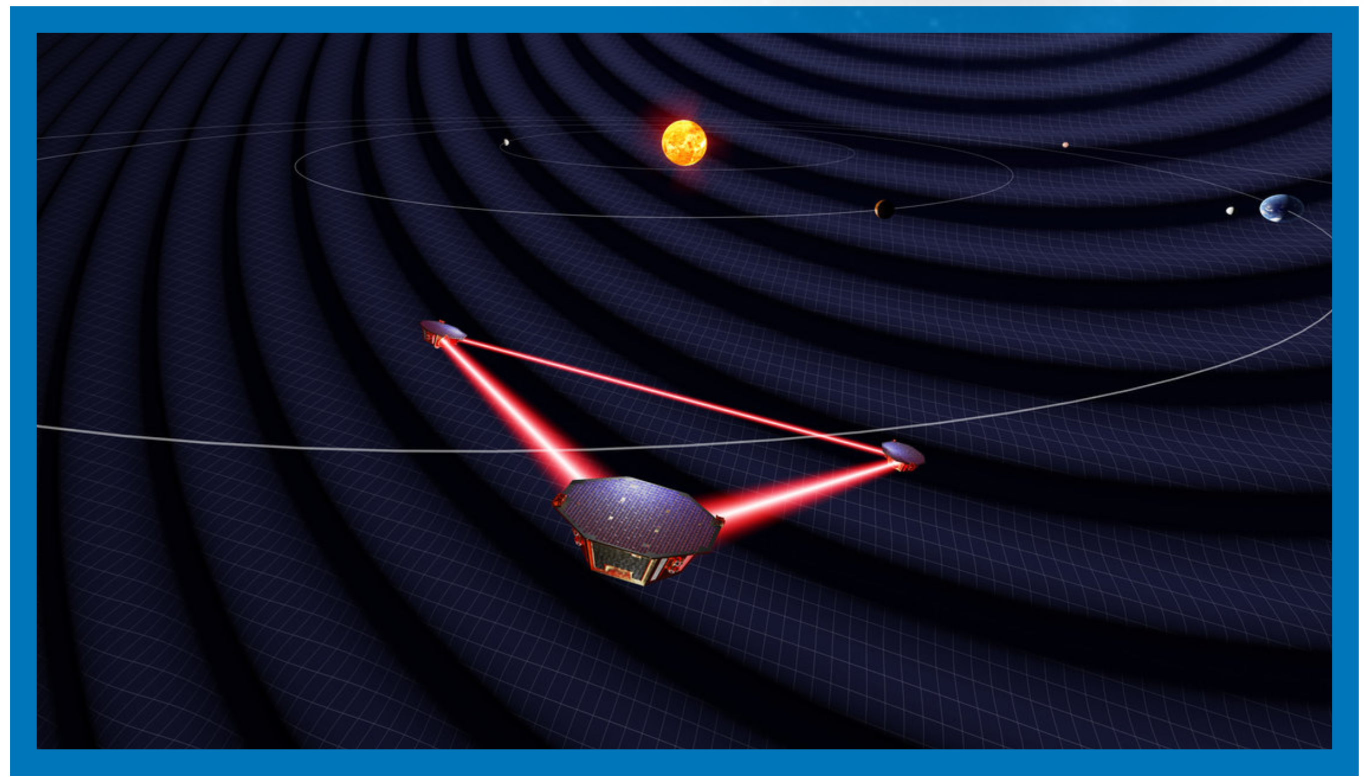
A golden age of data is coming- GW future detectors

© Cosmic Explorer









The challenge: A sparse and noisy inverse problem

For current observations:

- Sparse coverage of observables,
- Uncertainties and degeneracies.

For future observations:

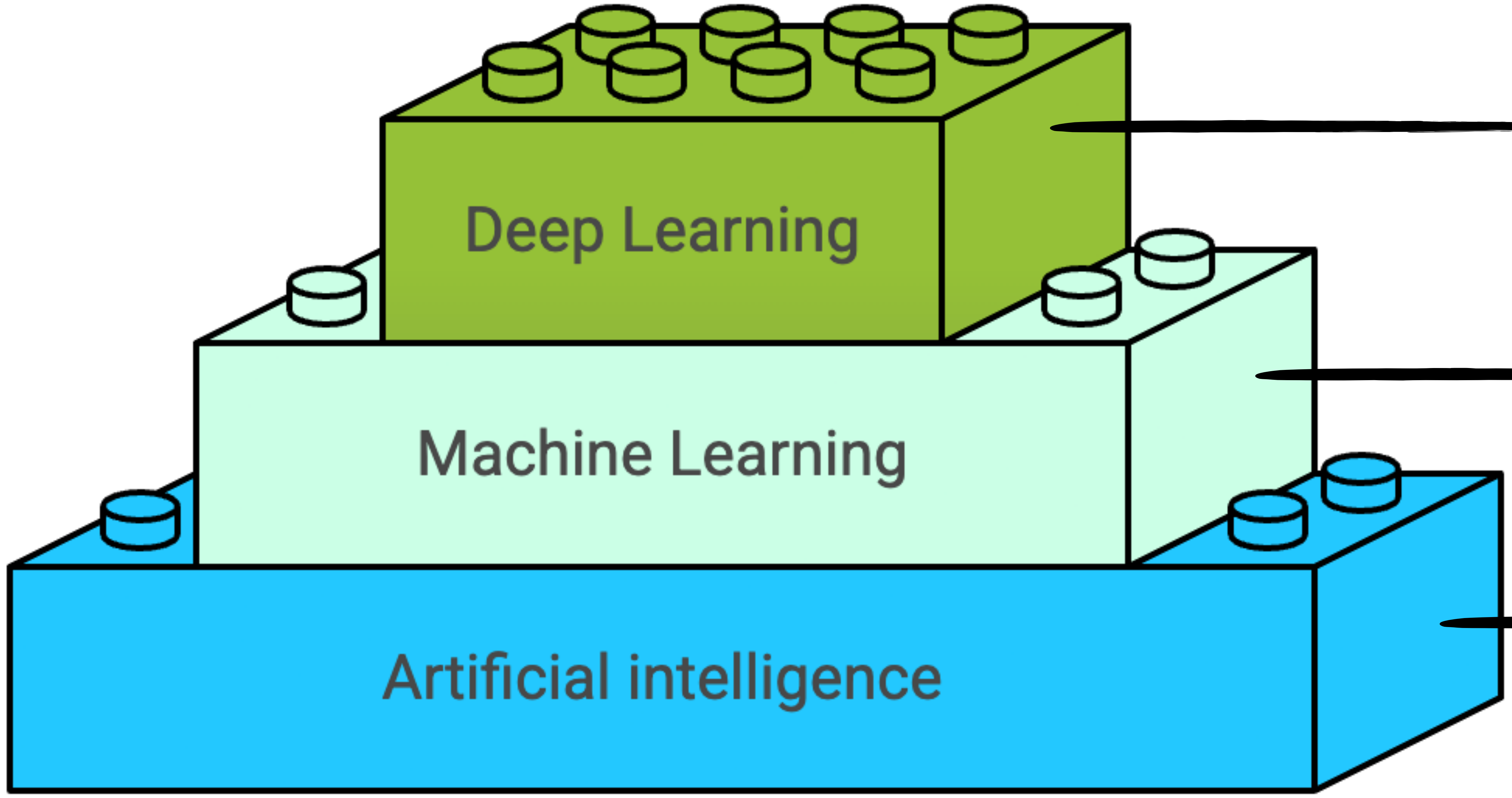
- Big amount of data,
- Smaller uncertainties, less degeneracies.

The solution, let’s talk about deep learning

What is Deep Learning?

,

, , ...

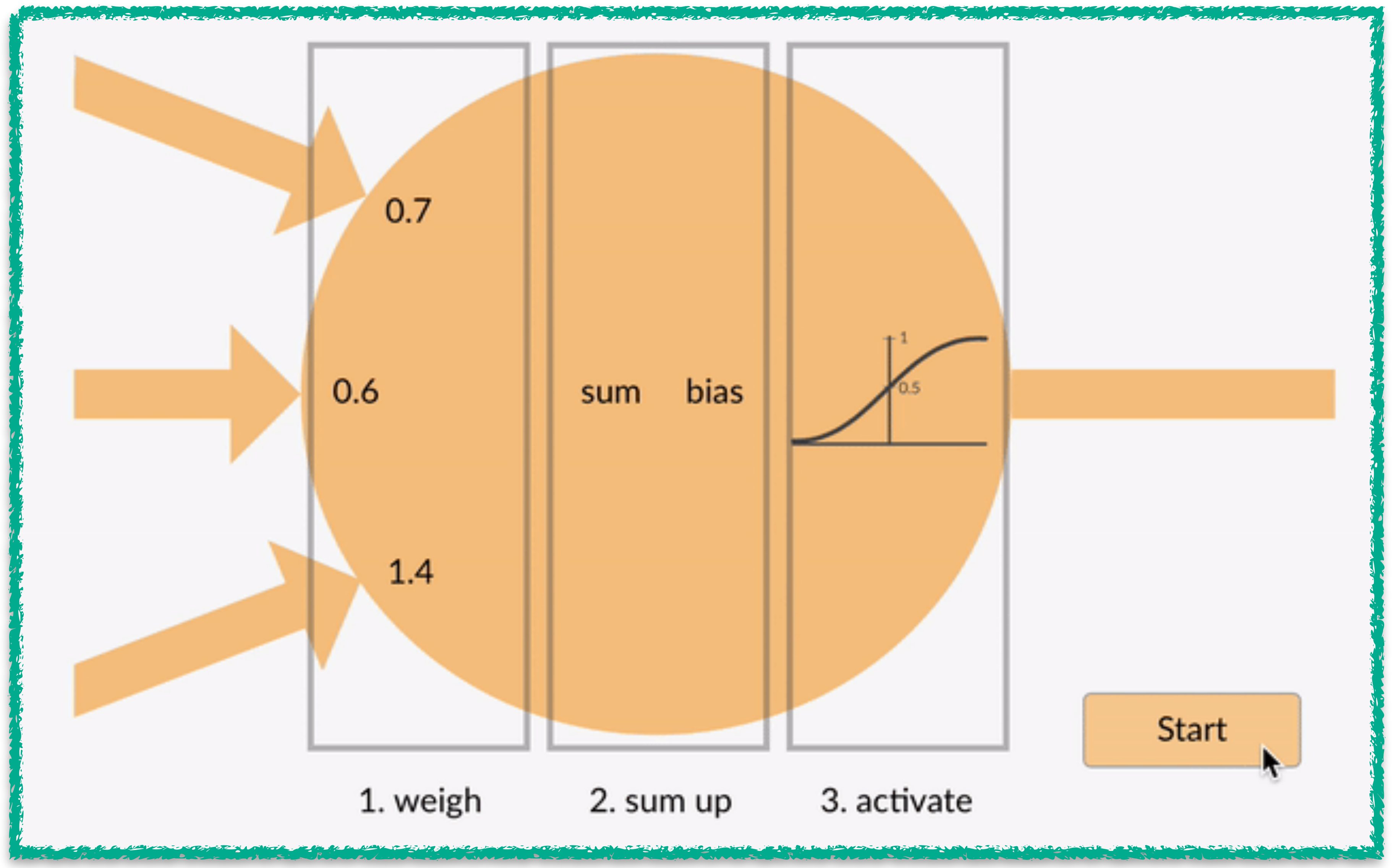


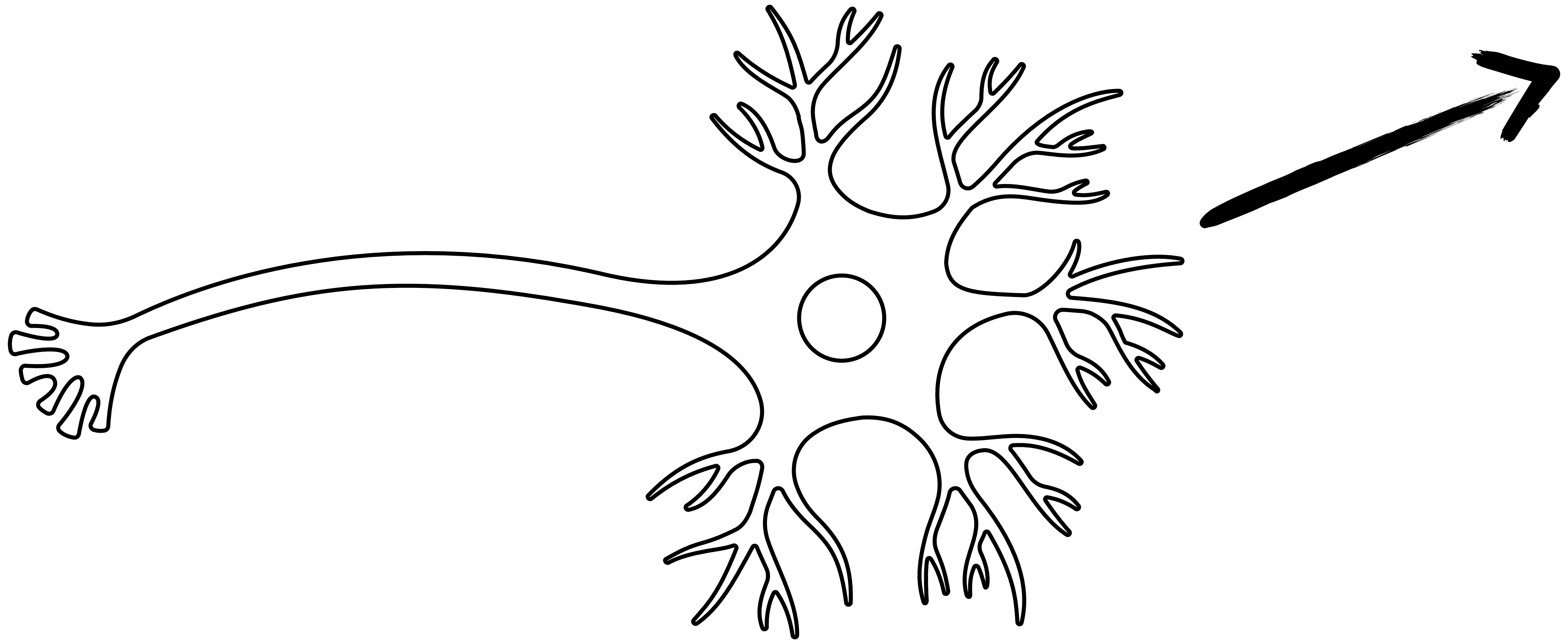
Machine learning algorithm with brain-like logic

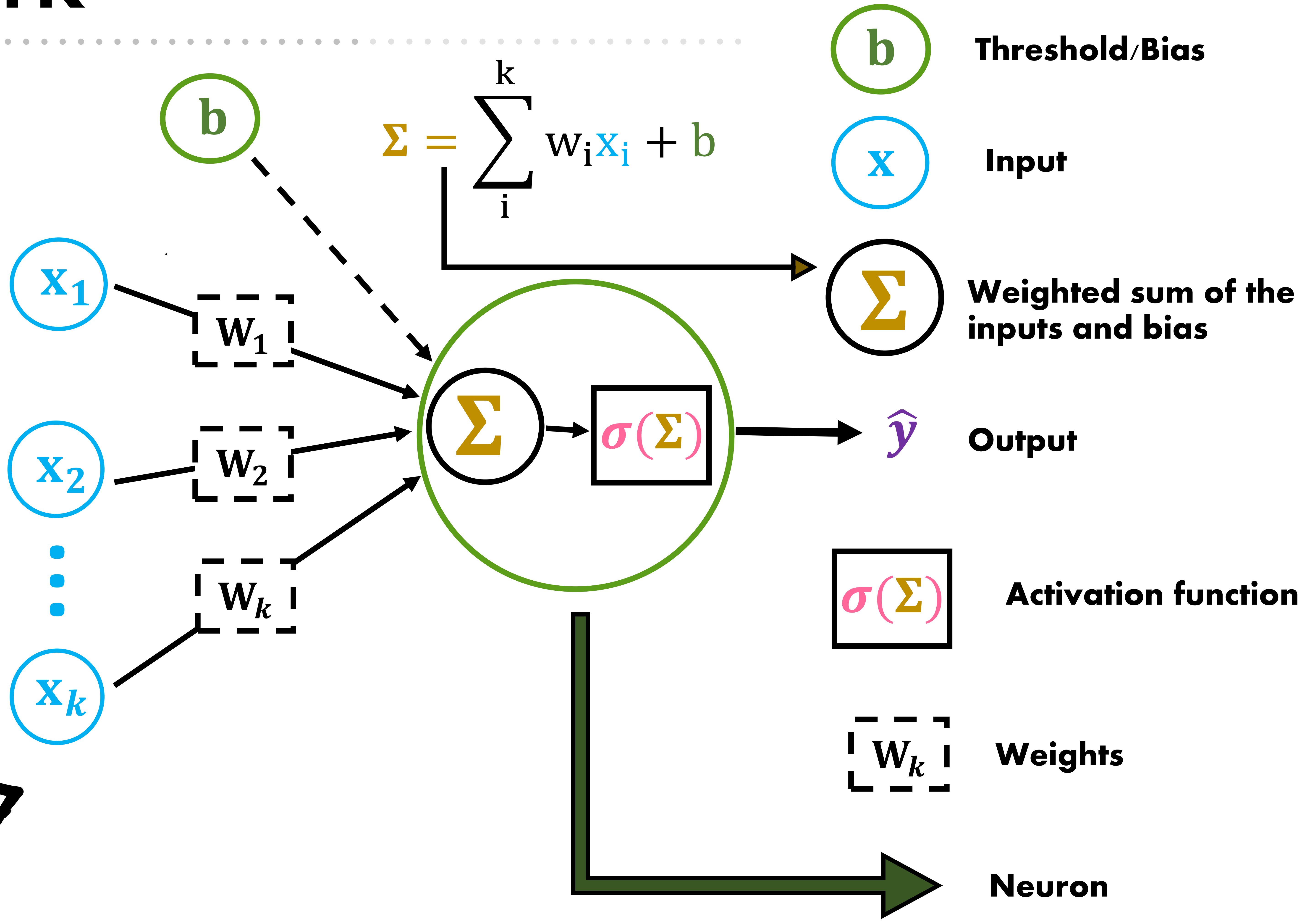
Algorithms which learn from data

Machines mimics human behavior

What is a Neural network







Deep Learning pipeline

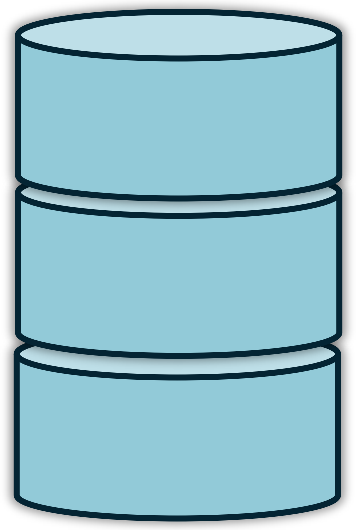
Benefits :

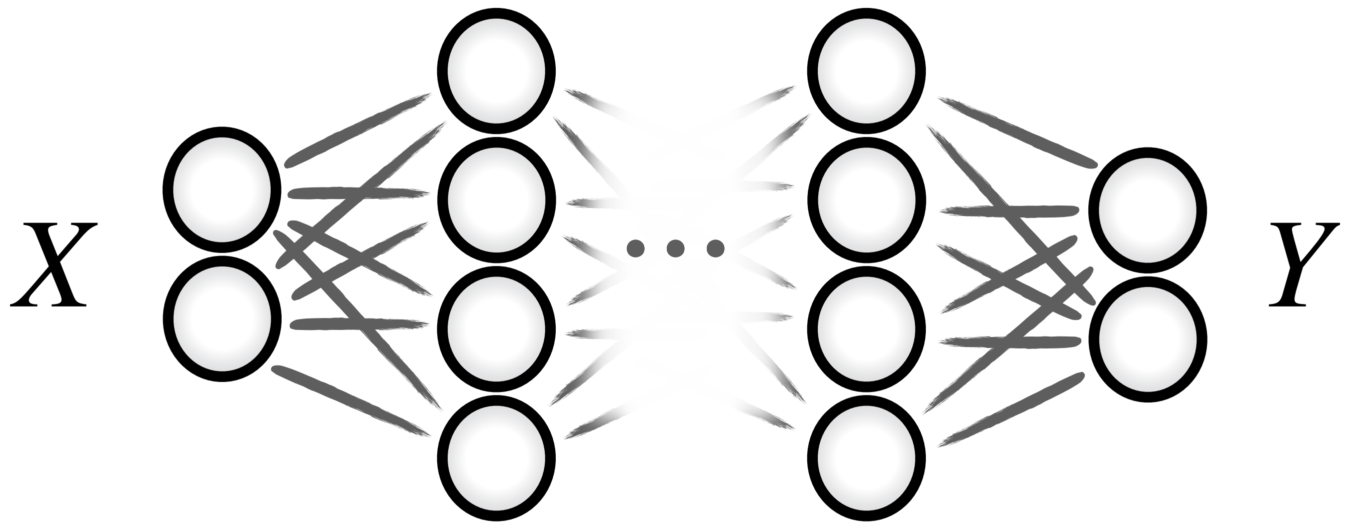
- Handles complexity,
- Extremely Fast,
- Quantifies Uncertainty.

$\approx$ **70%**
Prepare data

28%
Build and train models

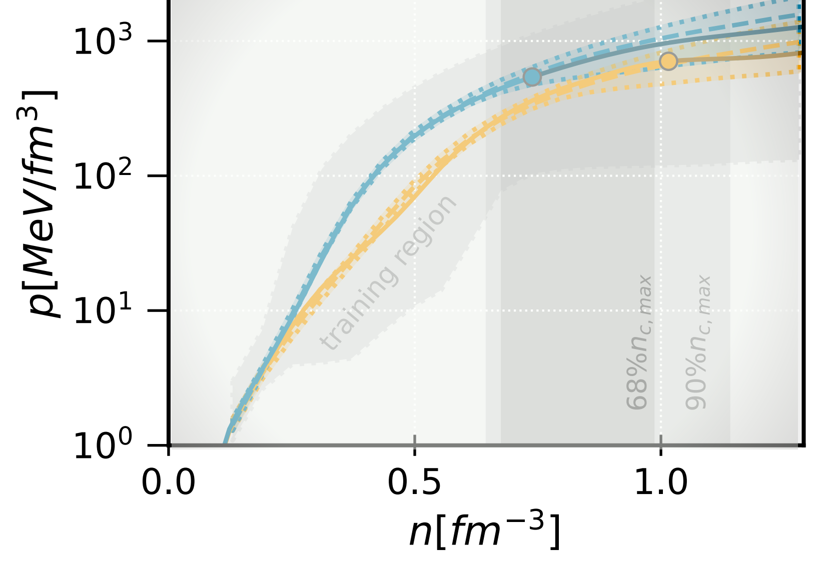
2%
Deploy and predict





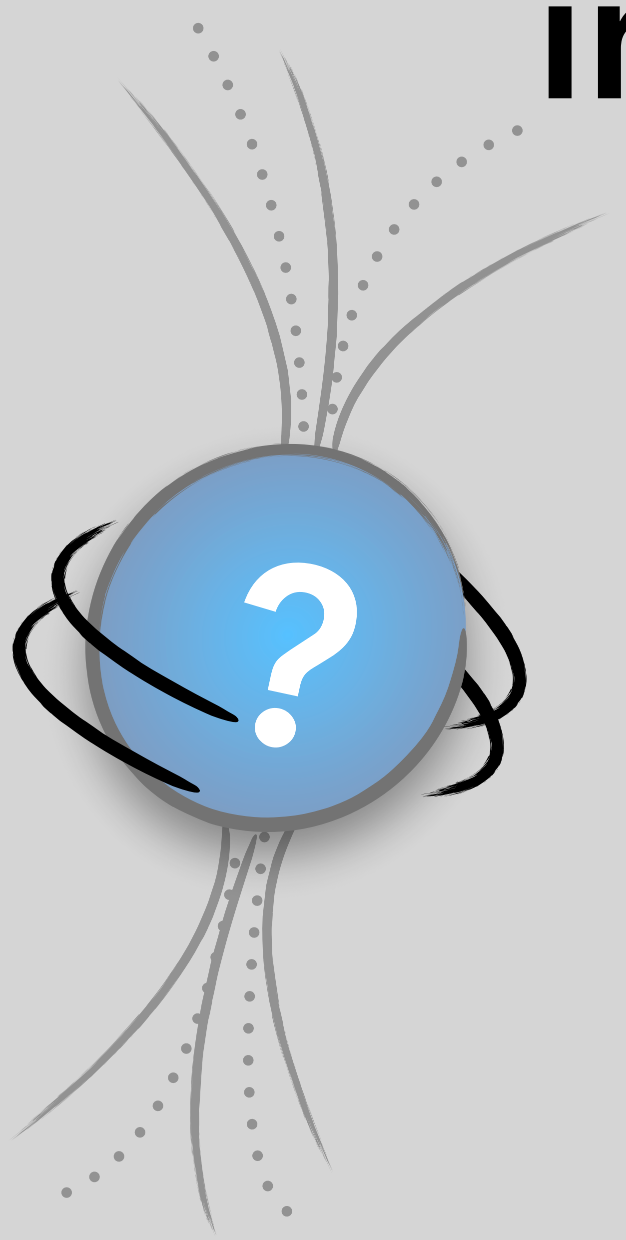
$f_\theta(x) : X \to Y$

Spoiler alert !

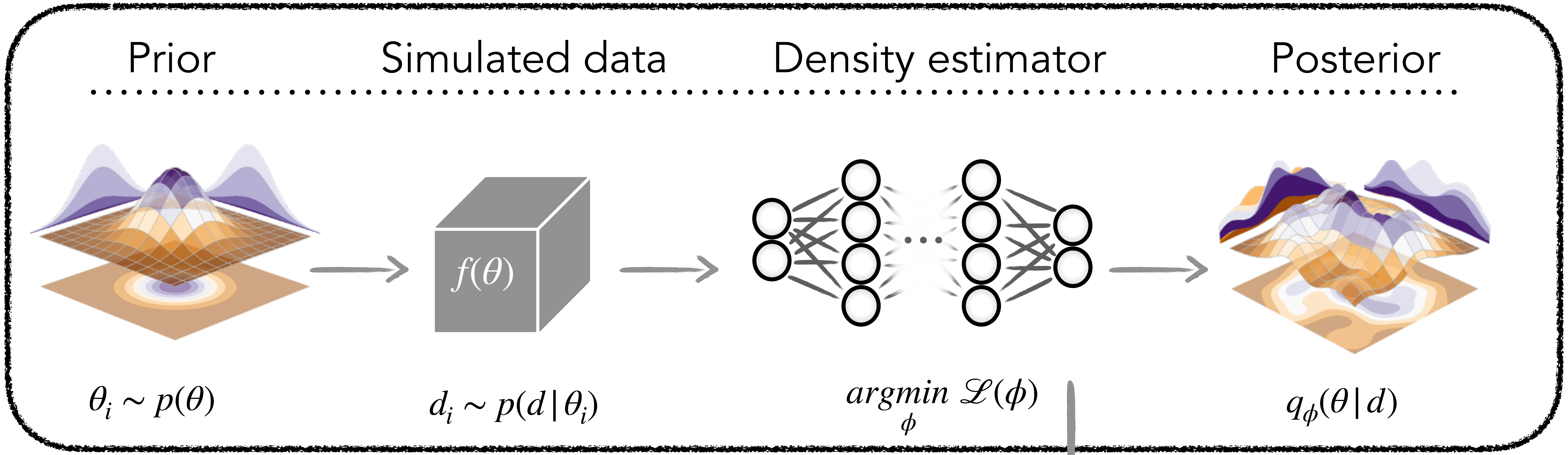


PRD **112,**083044

How effectively can Neural Posterior Estimation infer the Neutron Star Equation of State

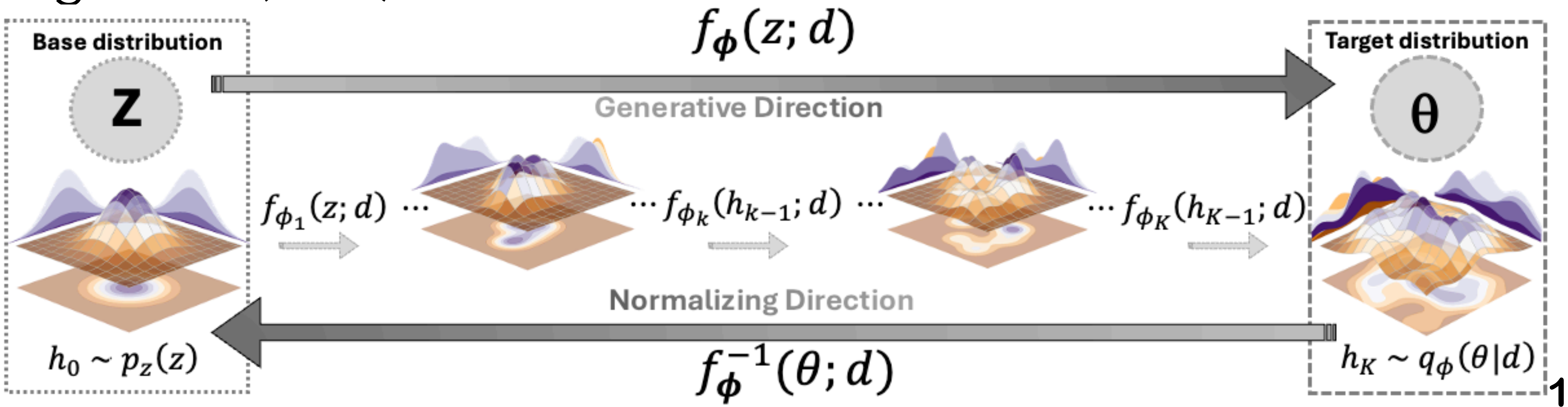


Neural posterior estimation



Conditional Normalizing Flows (CNF)

- ☑ Invertible
- ☑ Flexible
- ☑ Bijective



Quantities we aim to predict : $p(EoS\,|\,O)$

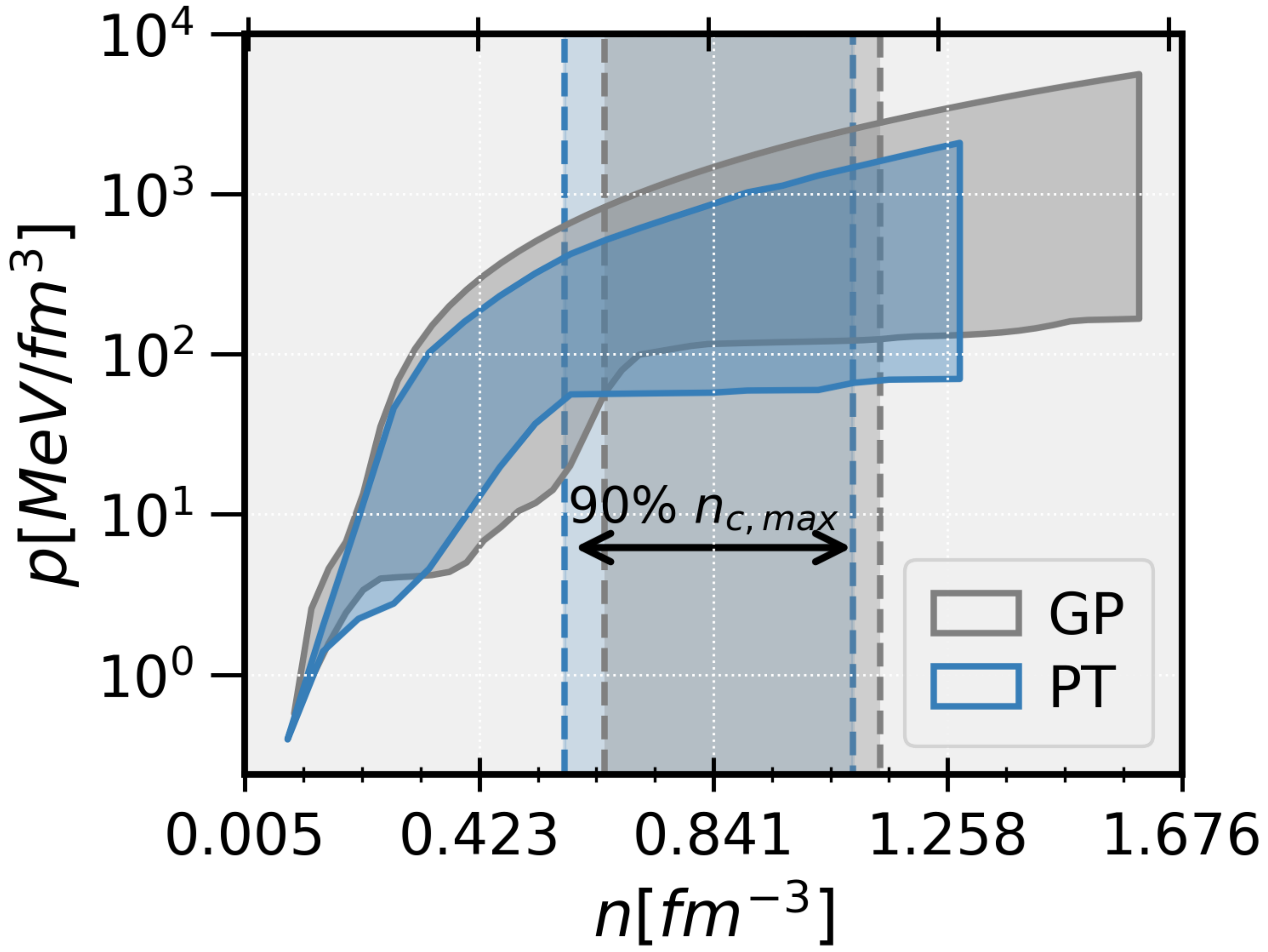
Two agnostic models :

Piecewise Polytropics (PT) PRD **111**,023035 (2025)

Gaussian Processes (GP) *Nat Commun* **14**, 8451 (2023)

The predicted physical quantities :

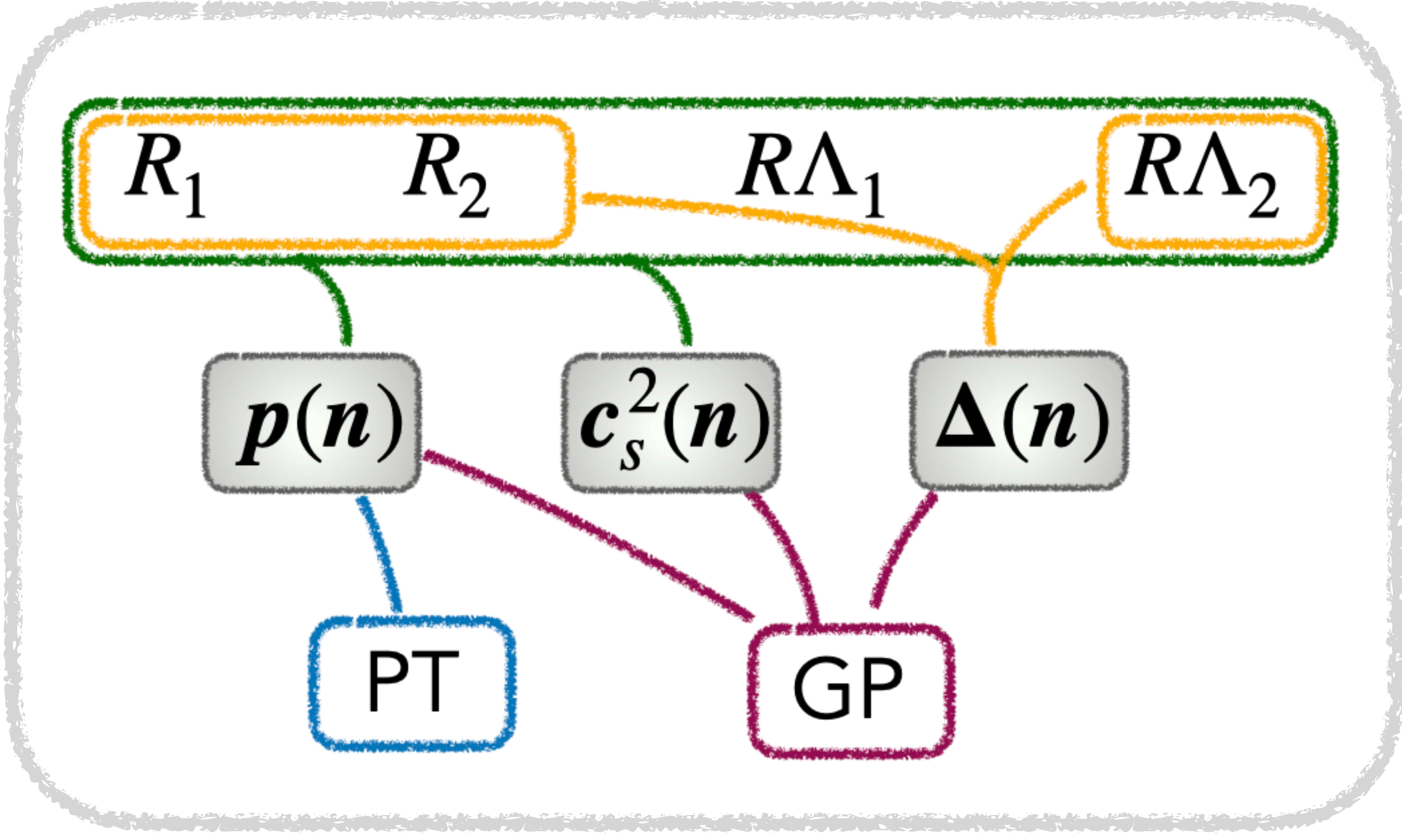
$$\begin{cases} \boldsymbol{p(n)} = [p(n_1), \cdots, p(n_{20})], \\ \boldsymbol{c_s^2(n)} = [c_s^2(n_1), \cdots, c_s^2(n_{20})], \\ \boldsymbol{\Delta(n)} = [\Delta(n_1), \cdots, \Delta(n_{20})], \end{cases}$$

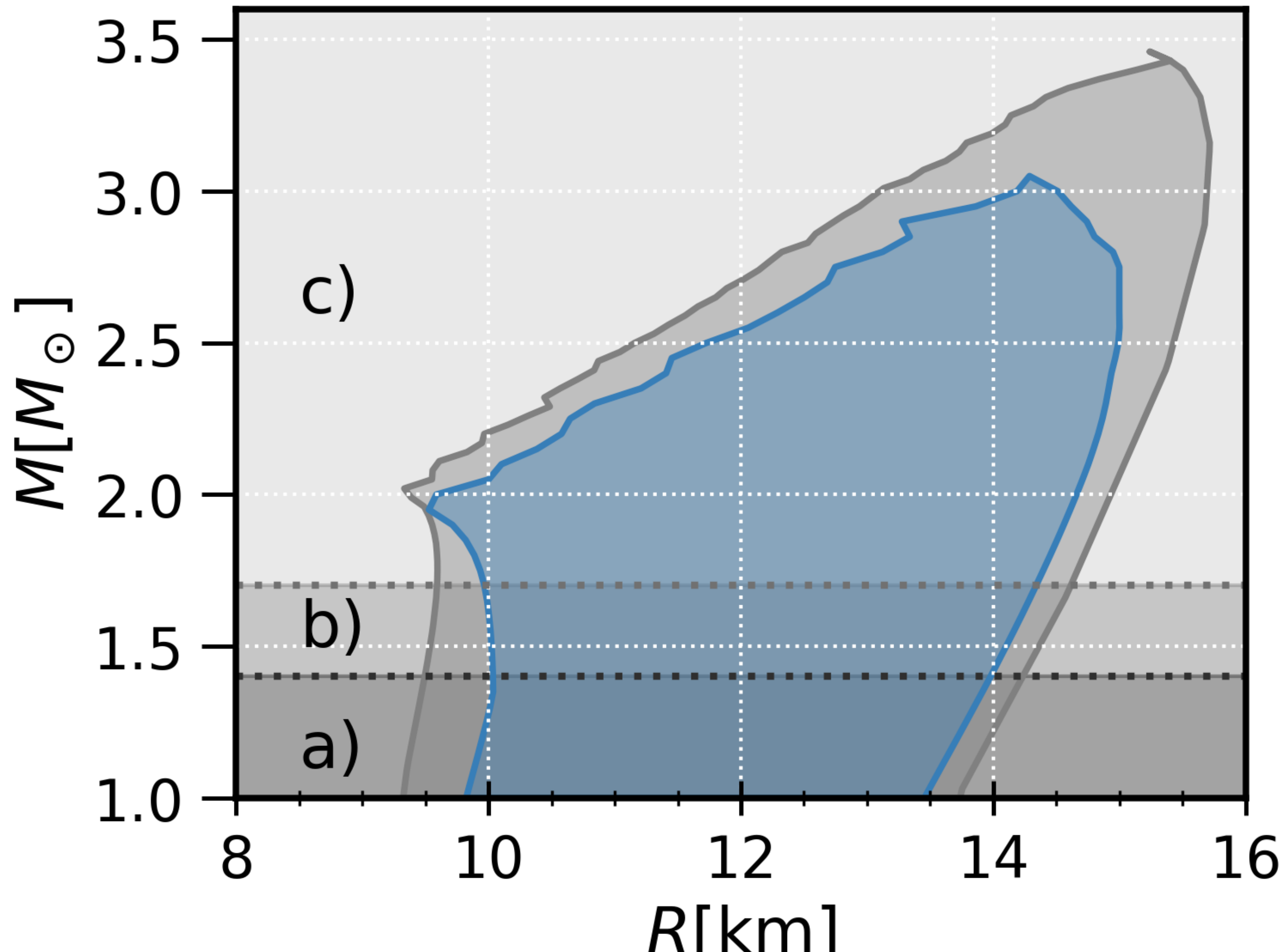


The conditioned quantities :

$$\begin{cases} R_x = [M_1, \cdots, M_{15}, R_1, \cdots, R_{15}],\ x \in [1,2] \\ R\Lambda_x = [M_1, \cdots, M_{15}, R_1, \cdots, R_{15}, M_1^*, \cdots, M_{15}^*, \Lambda_1, \cdots, \Lambda_{15}]\,. \end{cases}$$

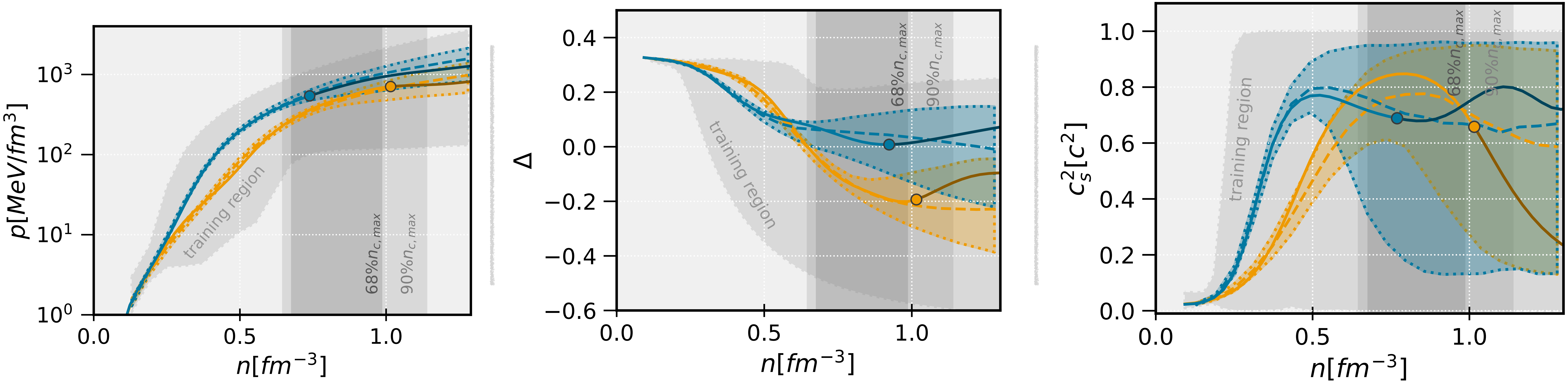
$x = 1$ without noise, $x = 2$ with gaussian noise.





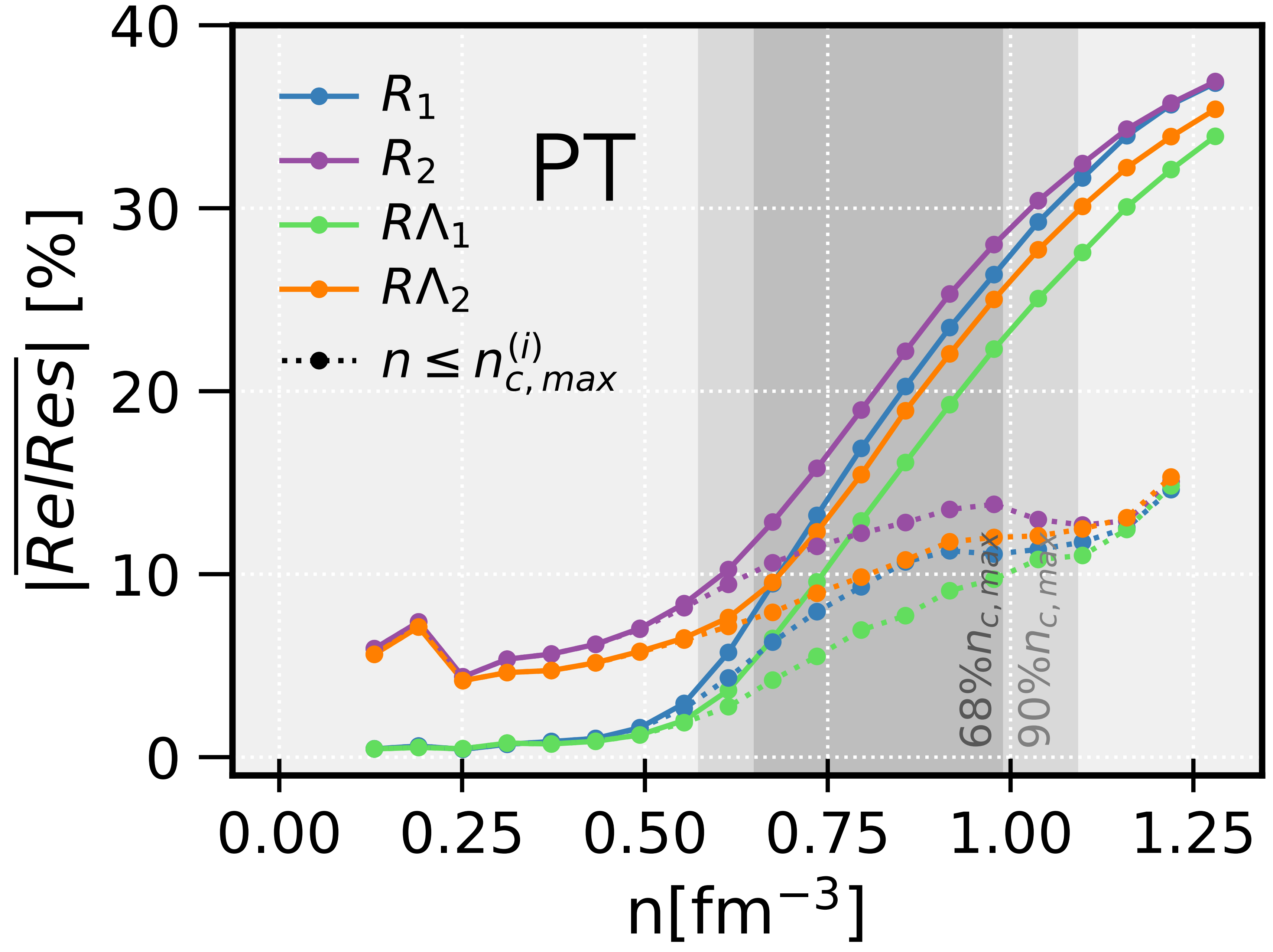
Key result: Accurate EoS reconstruction

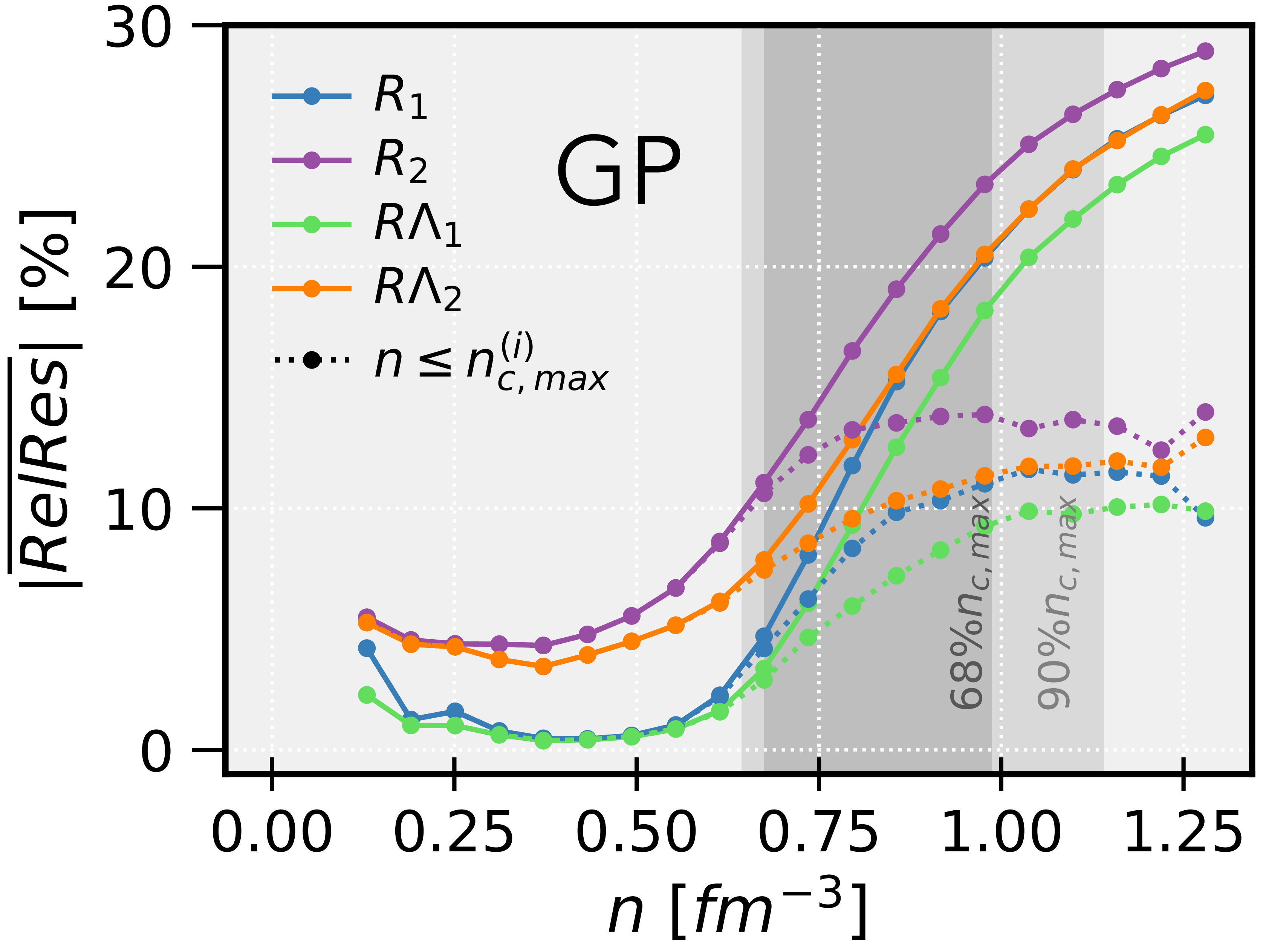
- Prediction for 2 samples of the test set $R\Lambda_2$ —, with a 90 % CI and median - - -,
- Increase in dispersion near maximum central density, represented by ●,
- Predictions always inside the CI.



Just for GP dataset

Relative error for pressure





$$\text{RelRes}^{(i)}(n) = \text{Med}_l \left[\frac{X_p^{(i,l)}(n) - X_T^{(i)}(n)}{X_T^{(i)}(n)} \right] \times 100$$

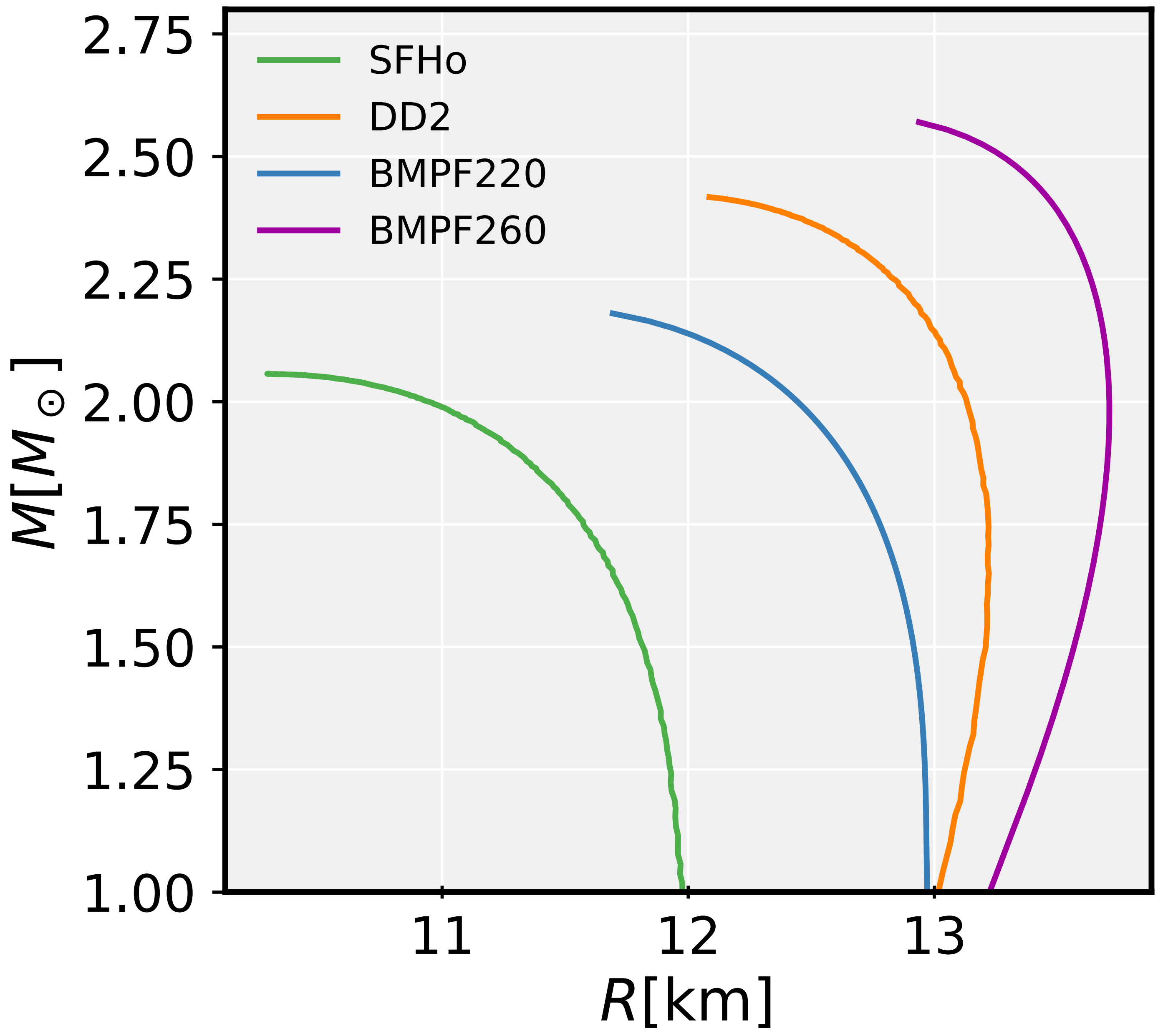
$$\begin{cases} |\overline{\text{RelRes}}|_{\leq n_{c,max}} = \text{Med}_i \left| \text{RelRes}^{(i)}(n) \right| \quad \text{for} \quad n \leq n_{c,max}^{(i)} . \\ |\overline{\text{RelRes}}| = \text{Med}_i \left| \text{RelRes}^{(i)}(n) \right| \quad . \end{cases}$$

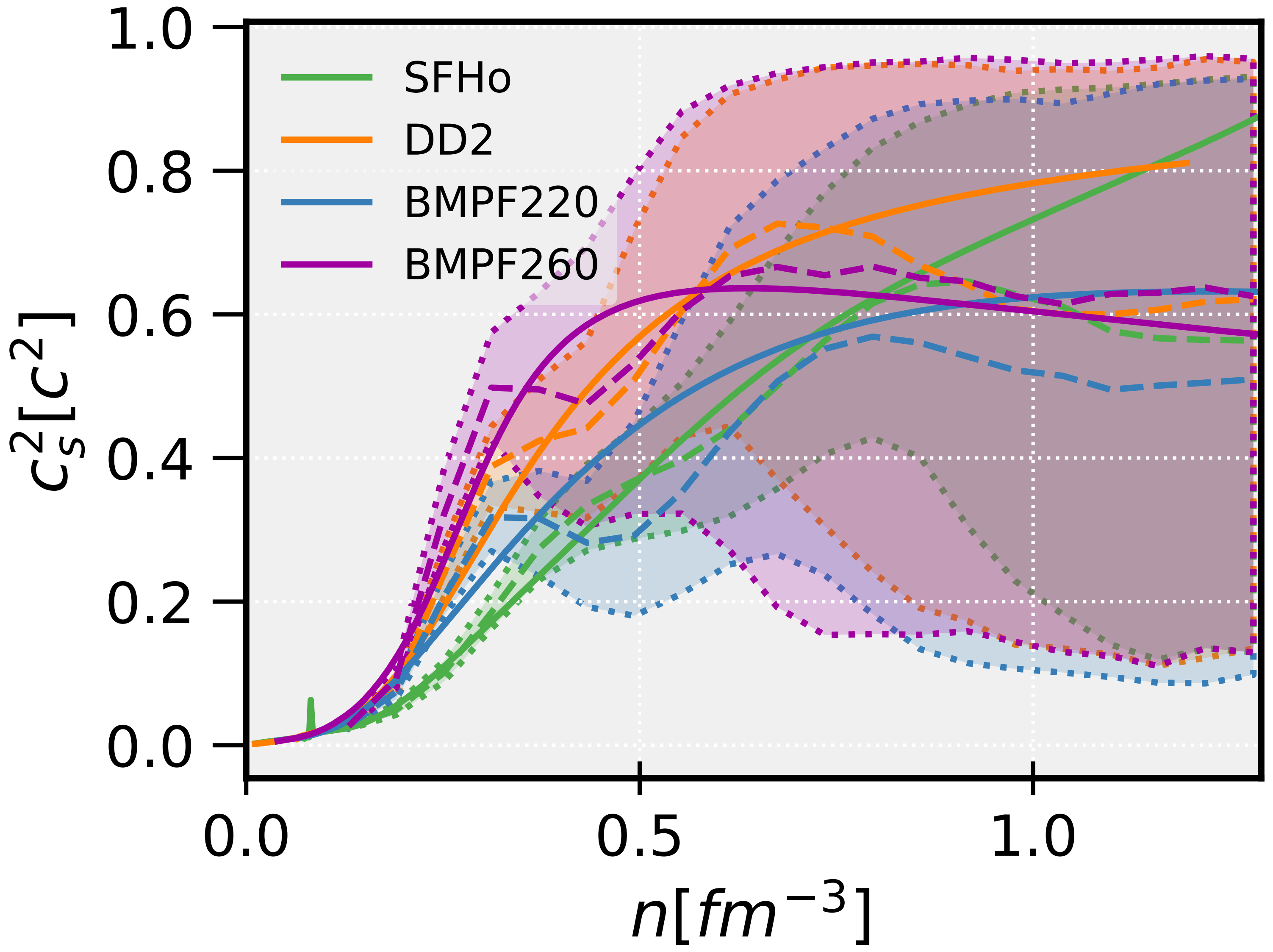
l = Posterior sample, i = EoS at density n

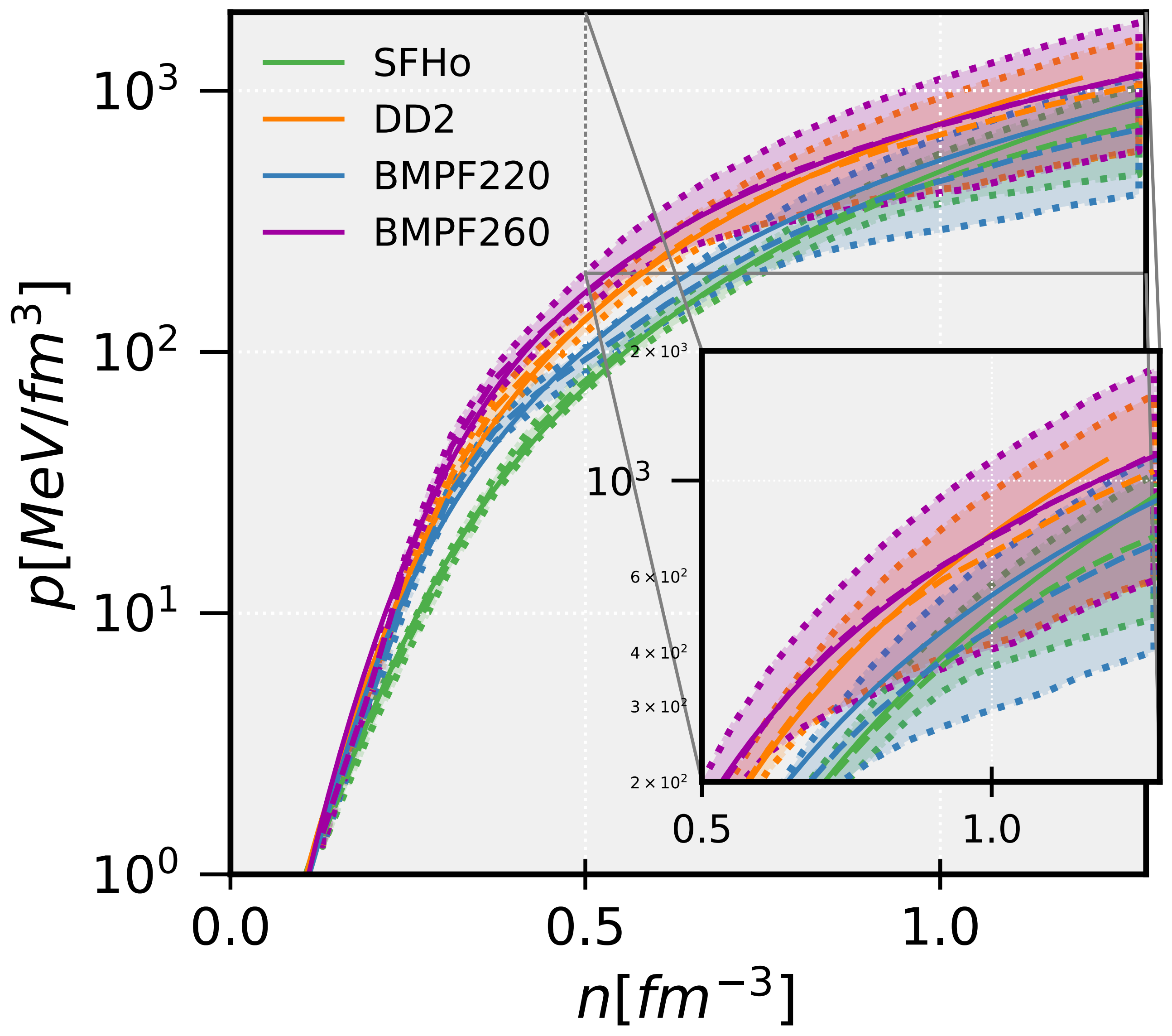
- Error increases with noise,
- Error decreases with tidal deformability,
- Error decreases when filtered for $n_{c,max}$.

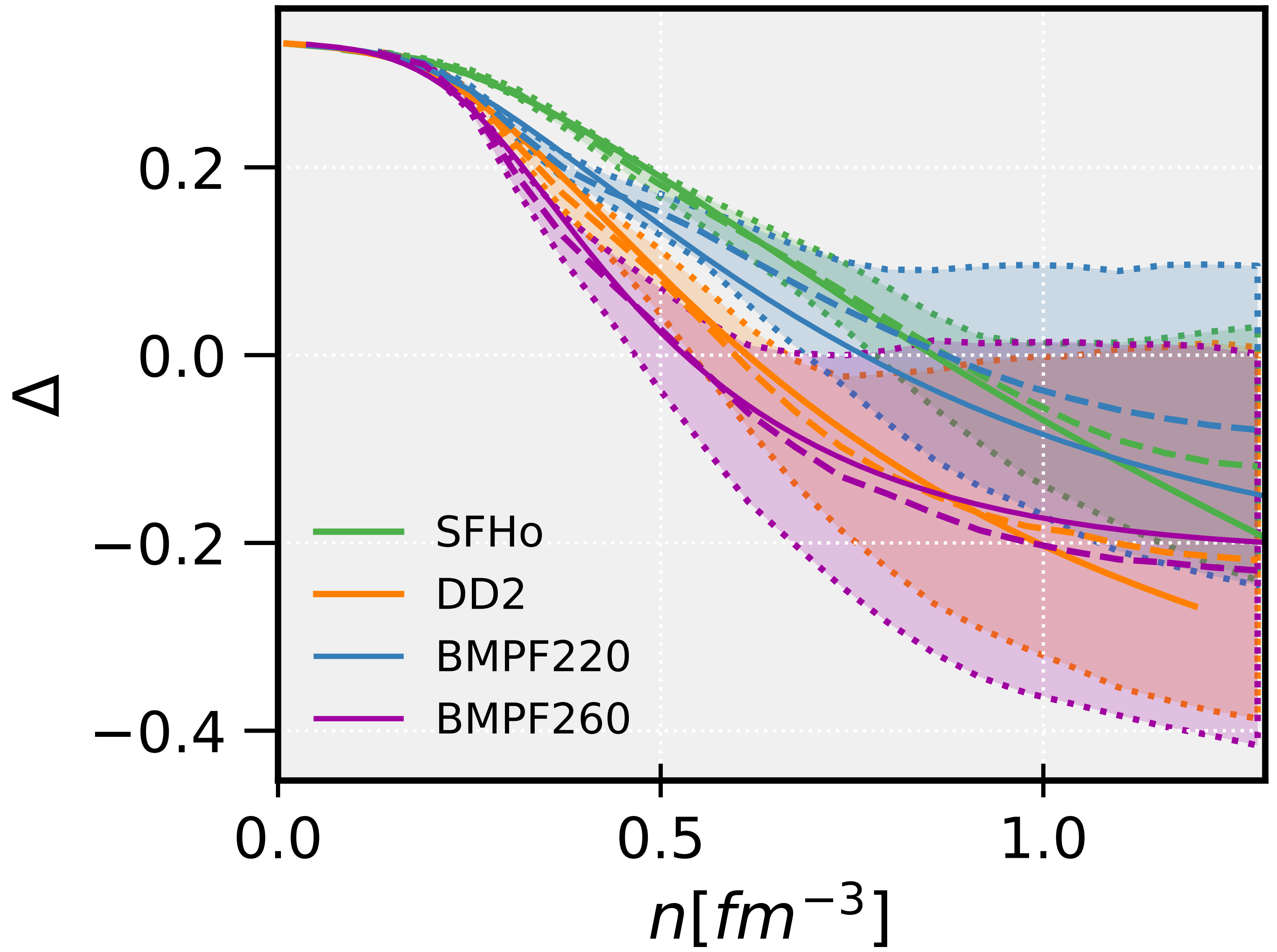
Another dataset inference test

- For the R_2 dataset we tested 4 EoS,
- Very different models.









Just for GP dataset

Summary

- Validation of neural posterior estimation,
- Crucial role of tidal deformability,
- Sensitivity to maximum central density,
- Uncertainty quantification.

The outlook: This method is well-suited for the upcoming "golden age" of multimessenger data, offering a promising tool to constrain dense matter physics.

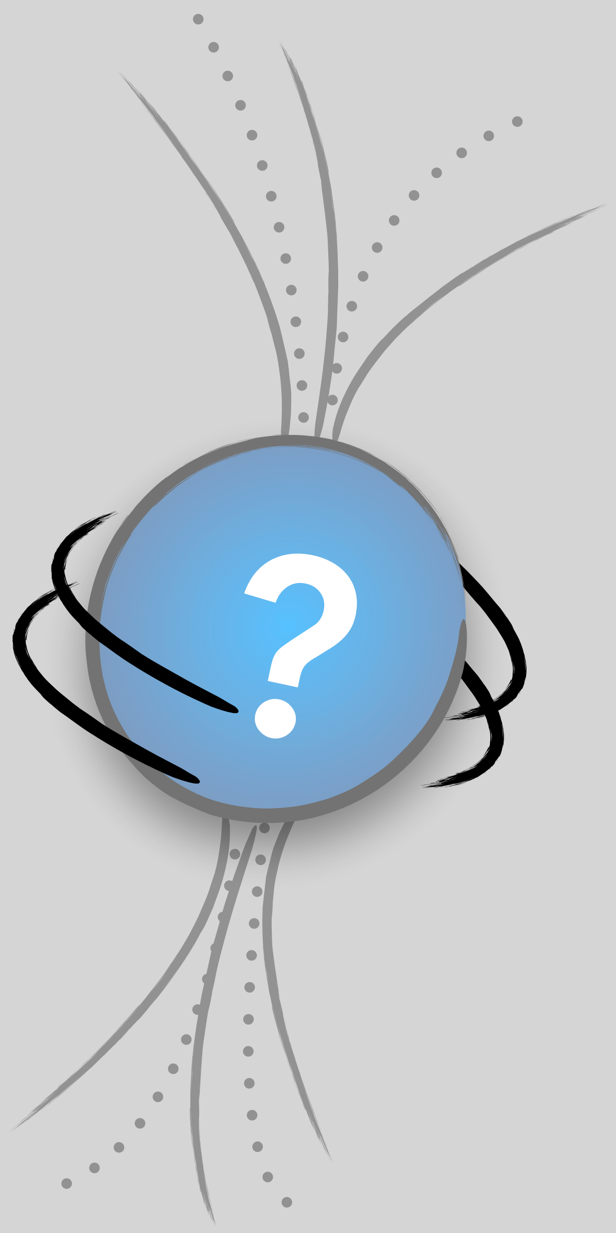
Still multiple open questions:

Do we have a phase transition?

What other particles do we have?

Do we have dark matter?

What is the particle fraction?



If you are curious about:

Understanding neutrons stars

+

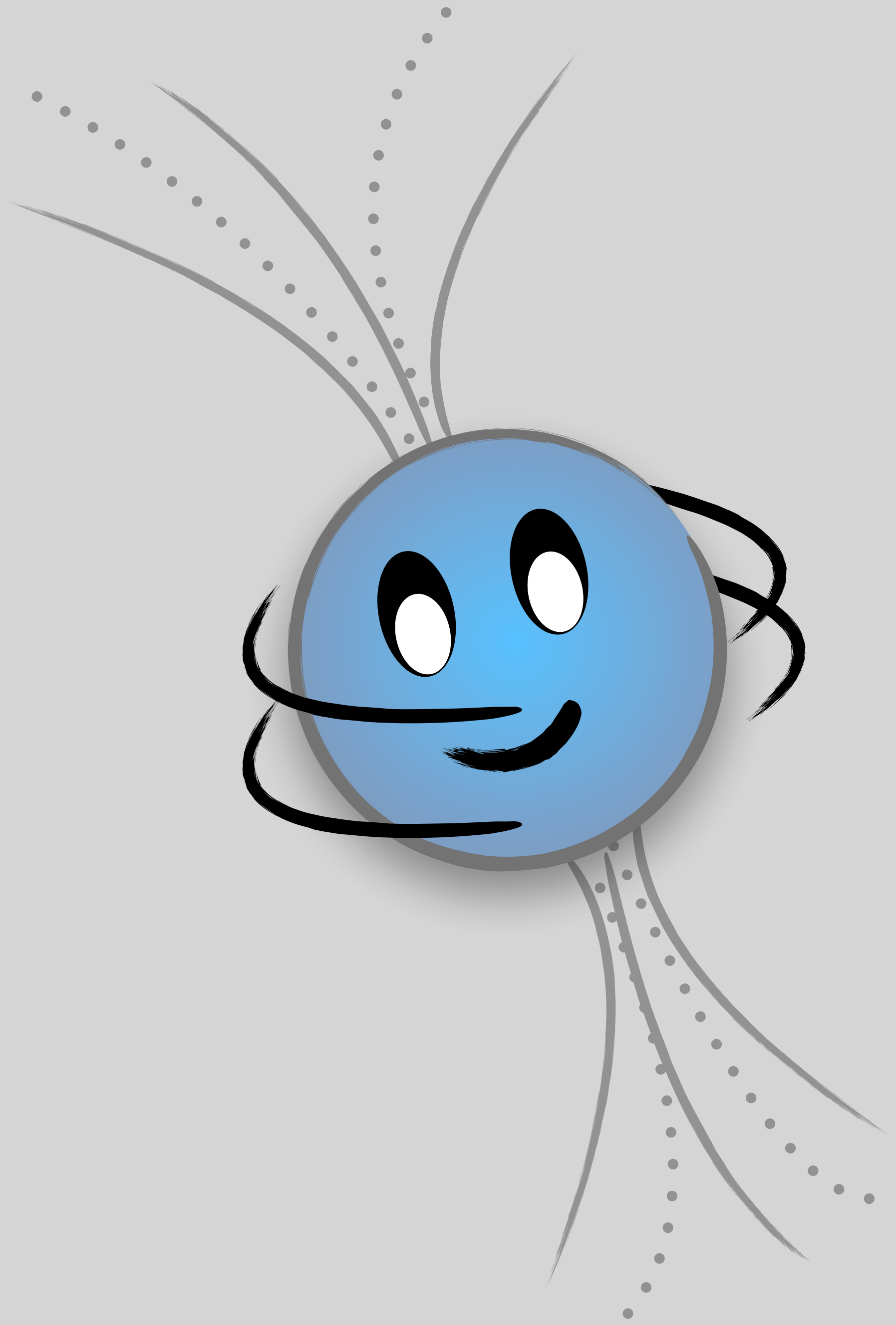
machine learning

If you want to swim in these waters

or

dive deeper into the unknown.

= Summer research opportunities available for bachelor and master students



Thank you for your attention

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