Neural networks estimation of the dense-matter equation of state from neutron-star observables

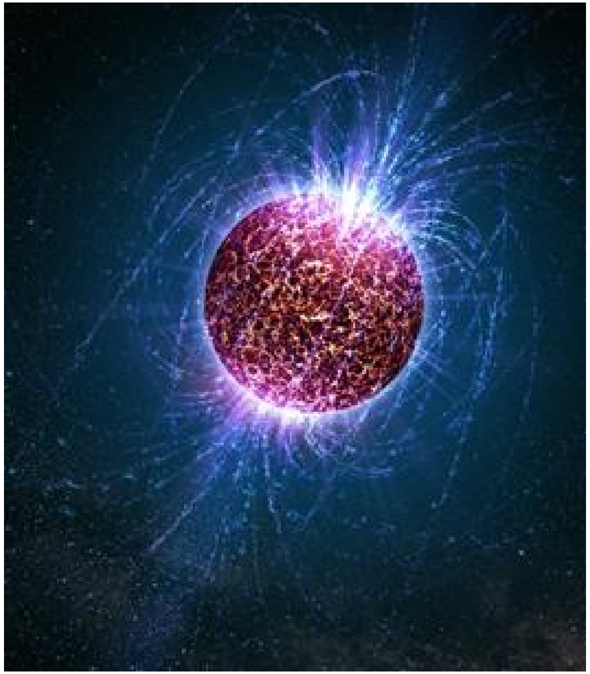
Filip Morawski, Michał Bejger
CAMK PAN

Bayesian Deep Learning Workshop, Paris

04.03.2020

Neutron stars

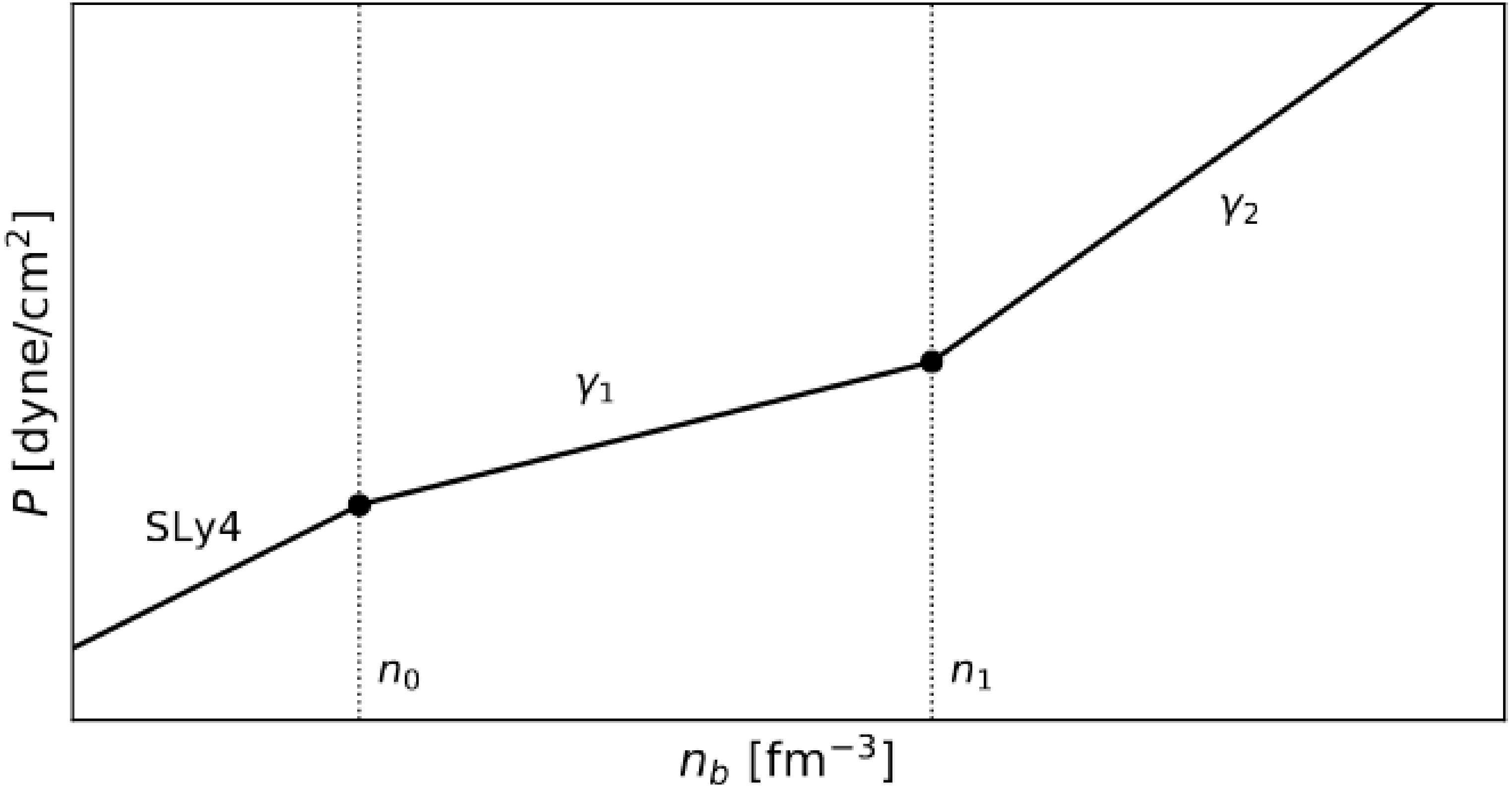
- Compact
- Dense
- Laboratory for extreme physics allowing studies of dense matter equation of state (EOS)



Neutron star EOS

- EOS is defined as the relation between star's density and pressure: $p(\rho)$ which can be translated into relation between between star radii and masses: $M(R)$ and/or mass and tidal deformability: $M(\Lambda)$
- There exist various models of EOS leading to different $M(R)$ relations. The *real* EOS is still unknown

Sample EOS



Tolman-Oppenheimer-Volkoff (TOV)

- Traditionally TOV equations are used on assumed EOS to obtain relations *M(R)* which are further compared with observations

$$\frac{dP}{dr}=\frac{-Gm}{r^2}\rho\left(1+\frac{P}{\rho c^2}\right)\left(1+\frac{4\pi r^3 P}{mc^2}\right)\left(1-\frac{2Gm}{rc^2}\right)^{-1}$$

Our project

We wanted to study:

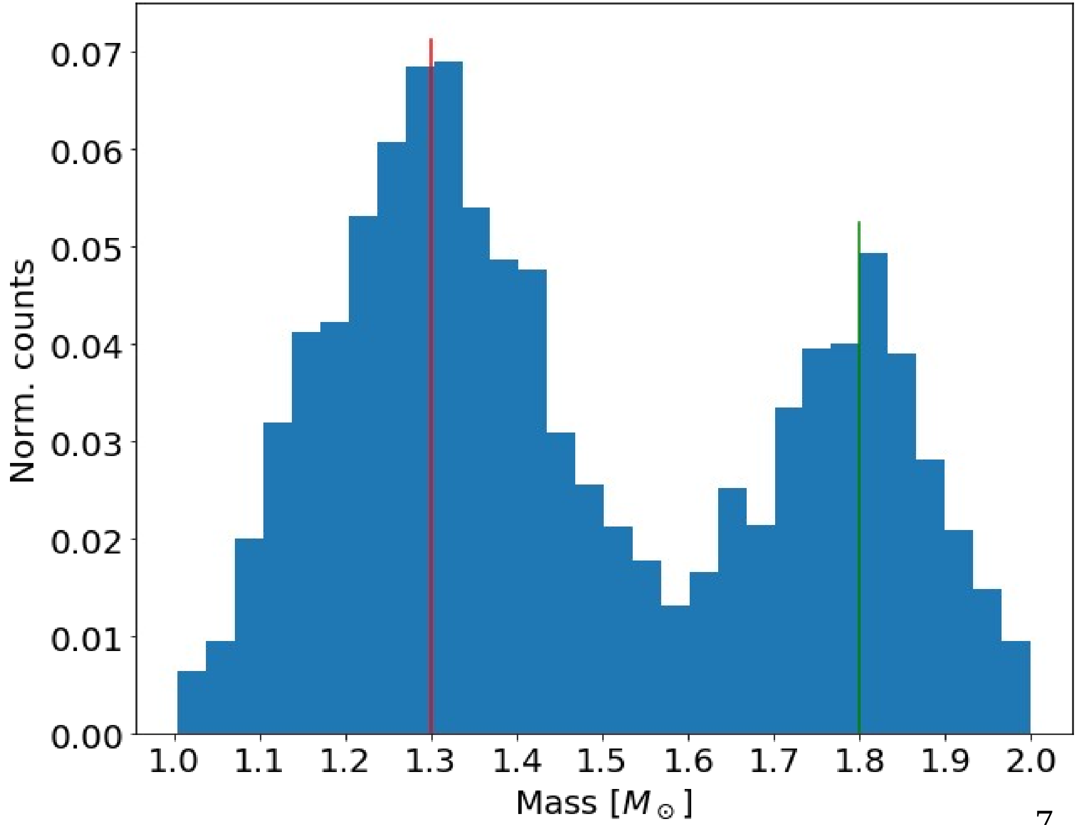
- Influence of neutron star mass distribution (uniform vs double gaussian)
- Influence of observations number
- Influence of measurement uncertainties

On the reconstruction of EOS

Neutron star mass

Mass range restricted to thea astrophysically-realistic range: [1, 2] M_solar.

It corresponds to the observed NS masses.

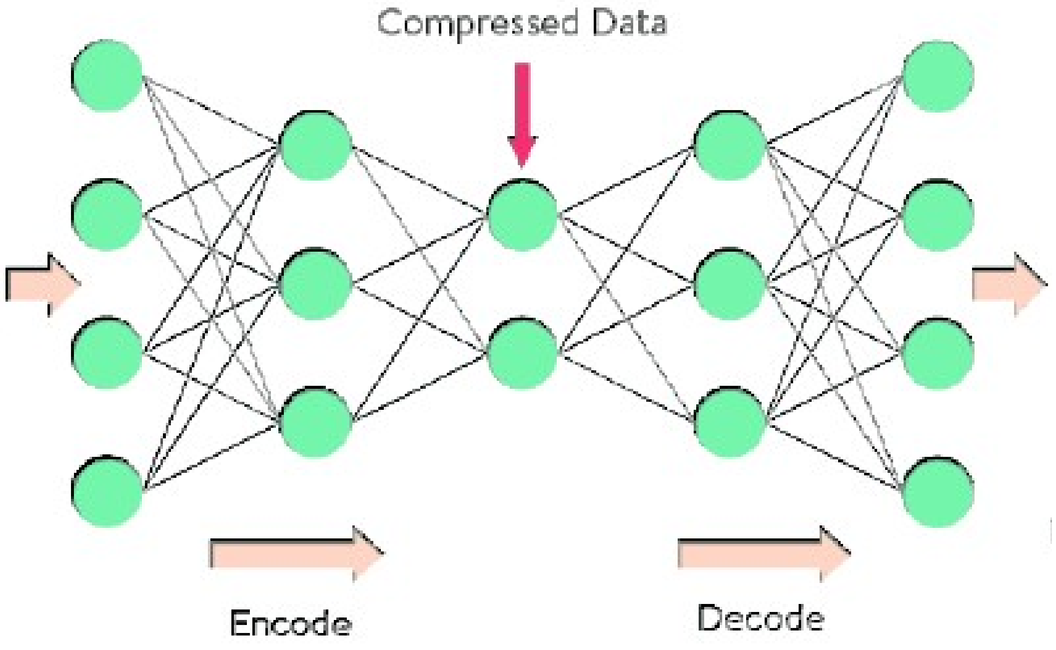


Autoencoder

$M(R)$

or

$M(\Lambda)$



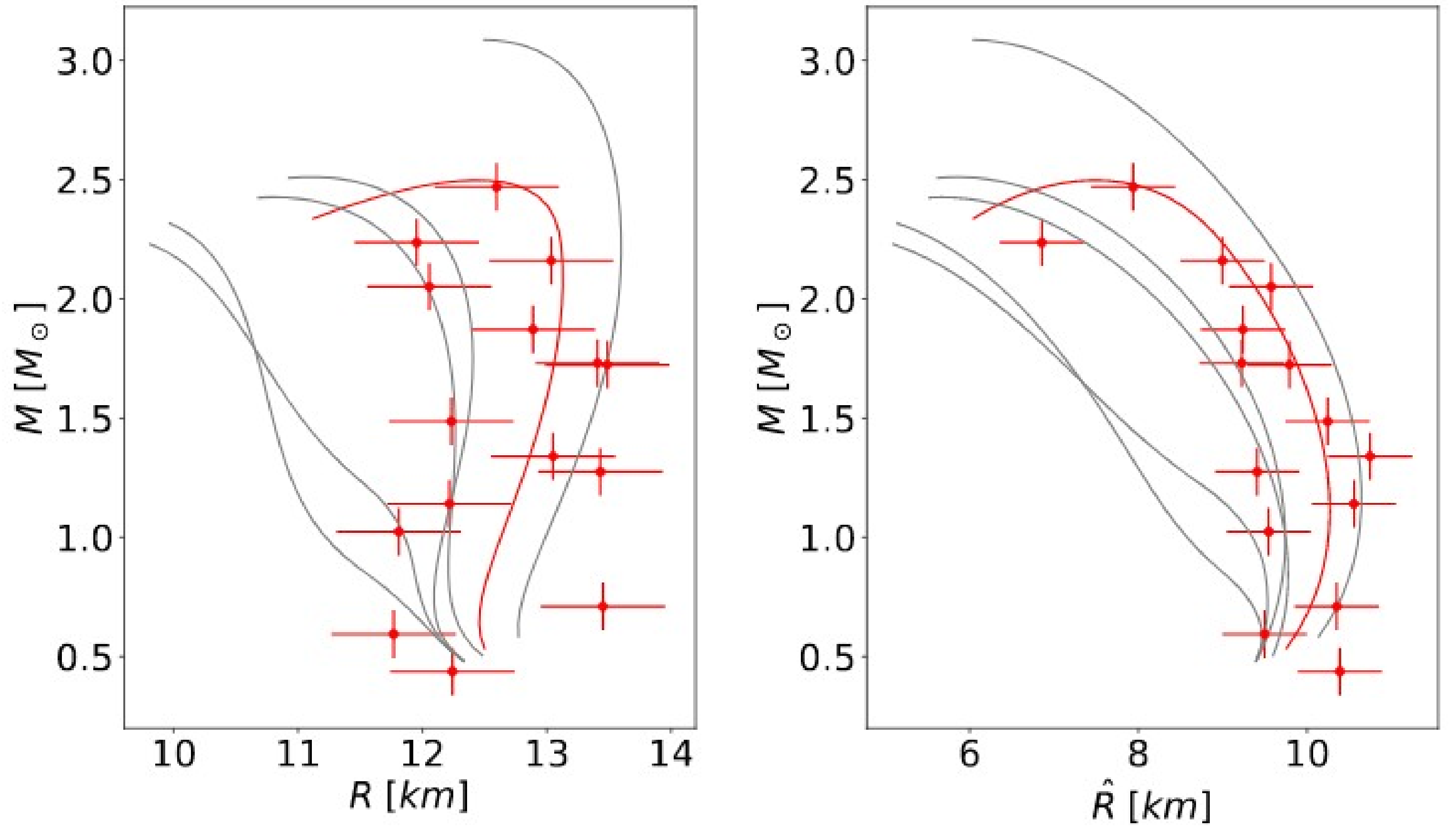
$p(\rho)$

Data

- Low-density part of EOS is adopted from existing astrophysical model (Sly4) up to particular baryon density n_0.
- This part is combined with piecewise relatyvistic polytrope:

$$P(n)=\kappa n^{\gamma} \qquad \rho c^2=\frac{P(n)}{\gamma-1}+n m_b c^2$$

Sample data



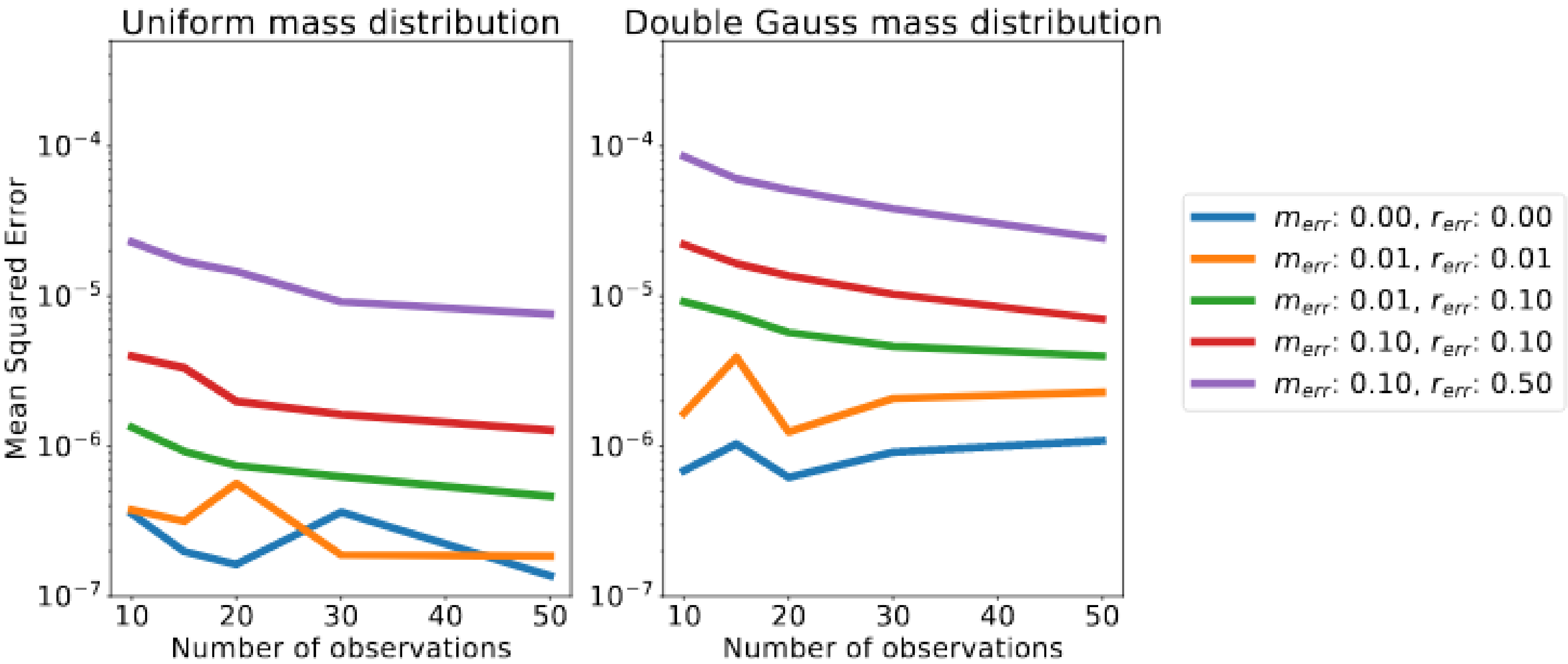
$$\hat{R} = 2\left(M\,\Lambda^{1/5}\right)$$

Reconstruction errors

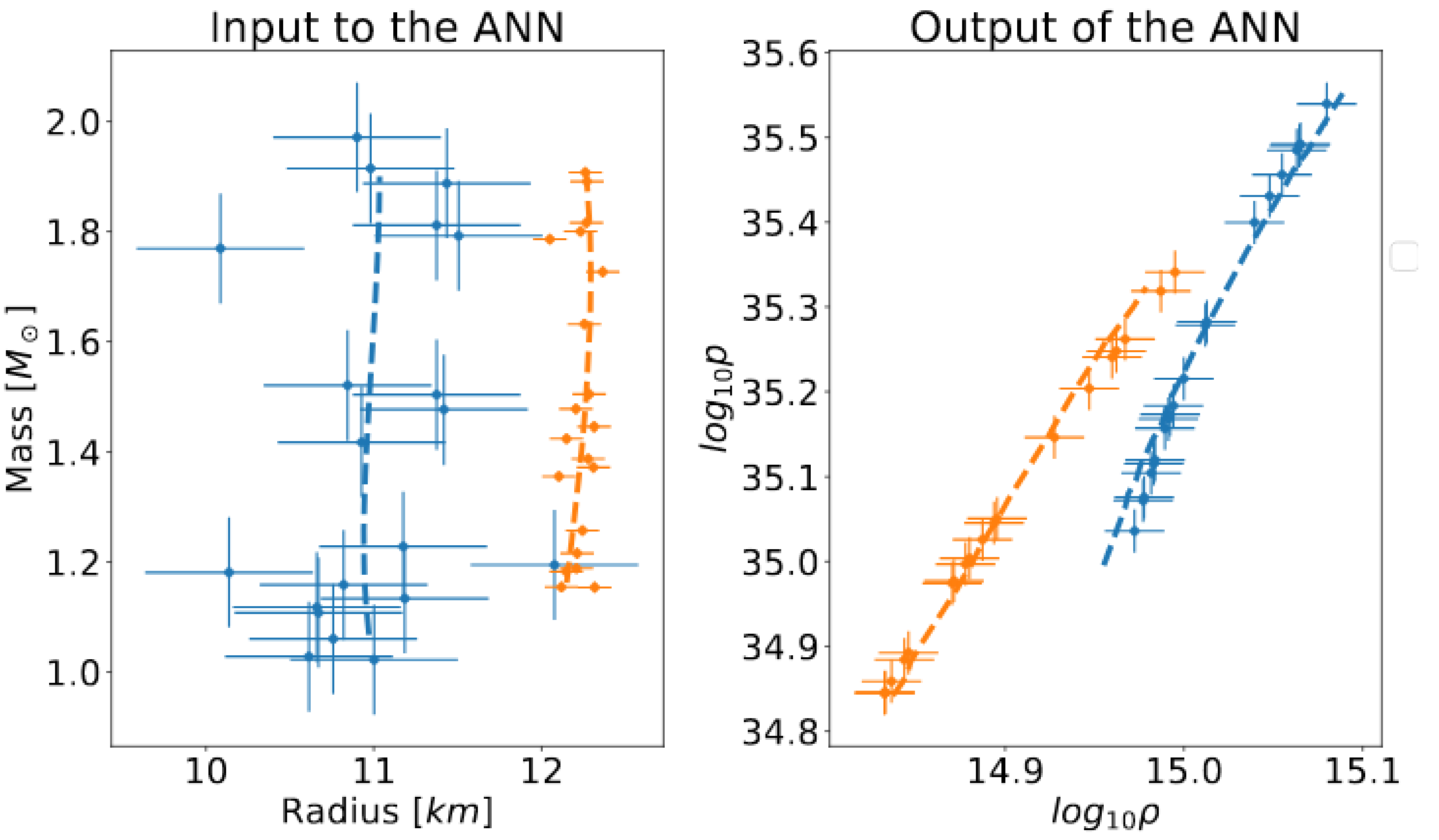
- We did not use loss function (Mean squared error)
- Instead for each polytrope we generated 30 different instances of data and computed reconstruction errors on EOS – the mean value for whole dataset is present on results

M(R) to EOS

M(R) to EOS - loss

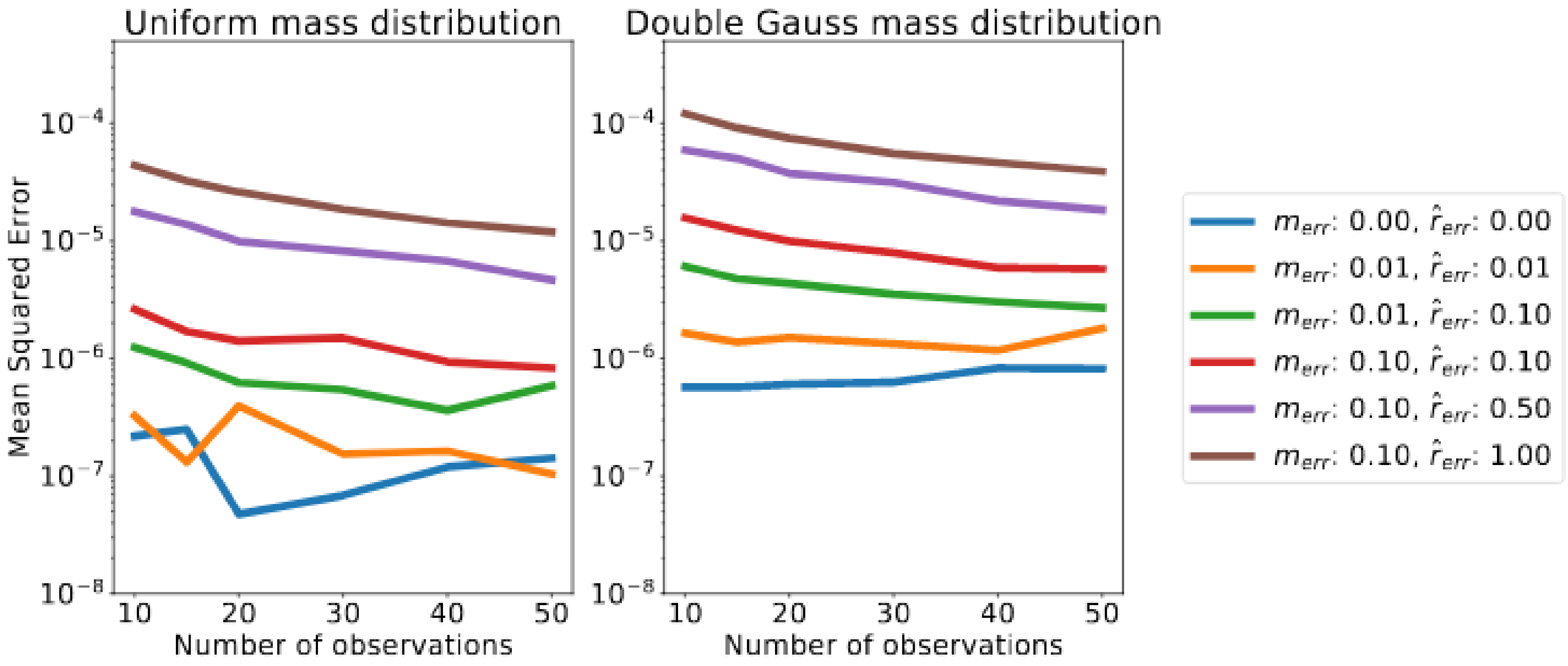


M(R) to EOS - reconstruction

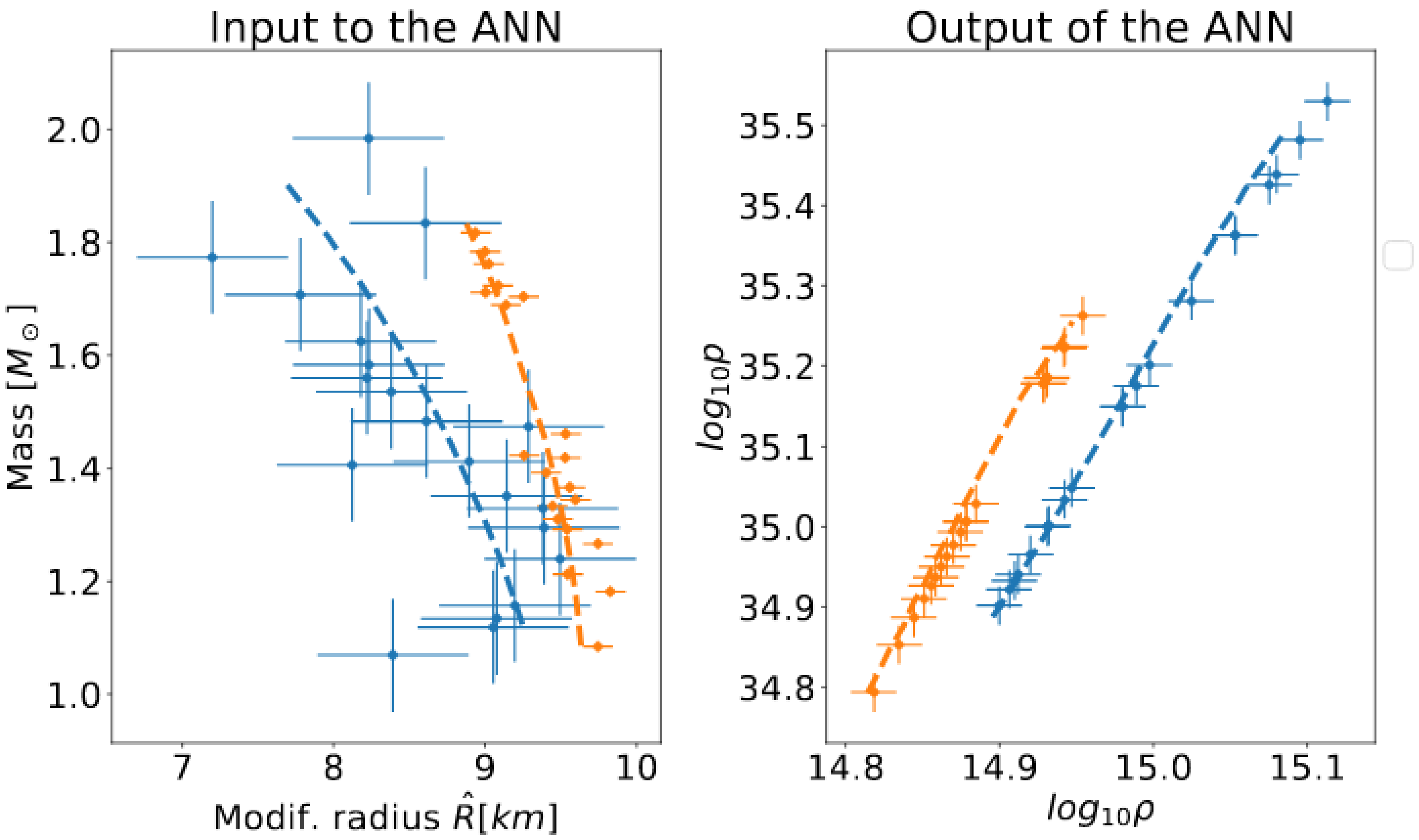


$M(\hat{R})$ to EOS

M(R̂) to EOS - loss

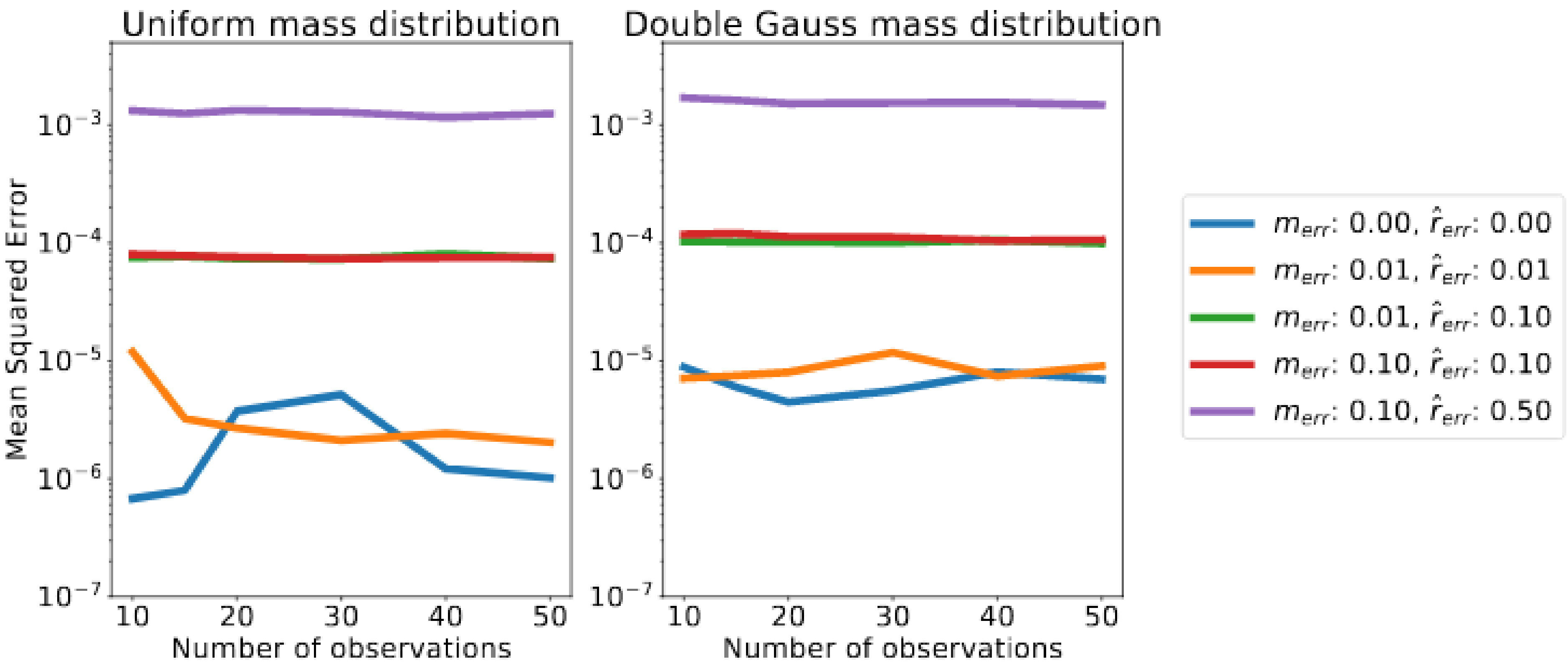


M(R̂) to EOS - reconstruction

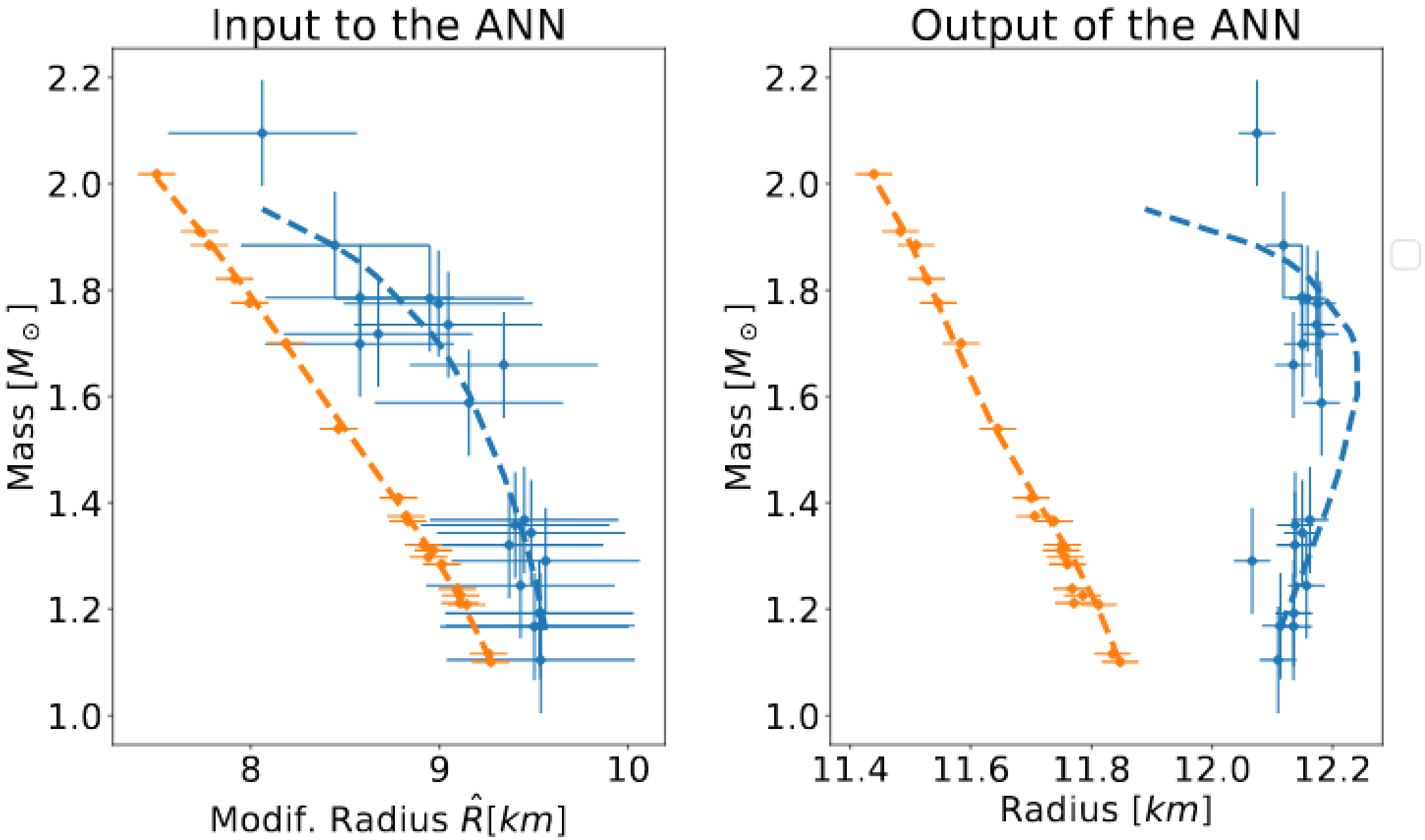


M($\hat{R}$) to R

M(R̂) to R - loss

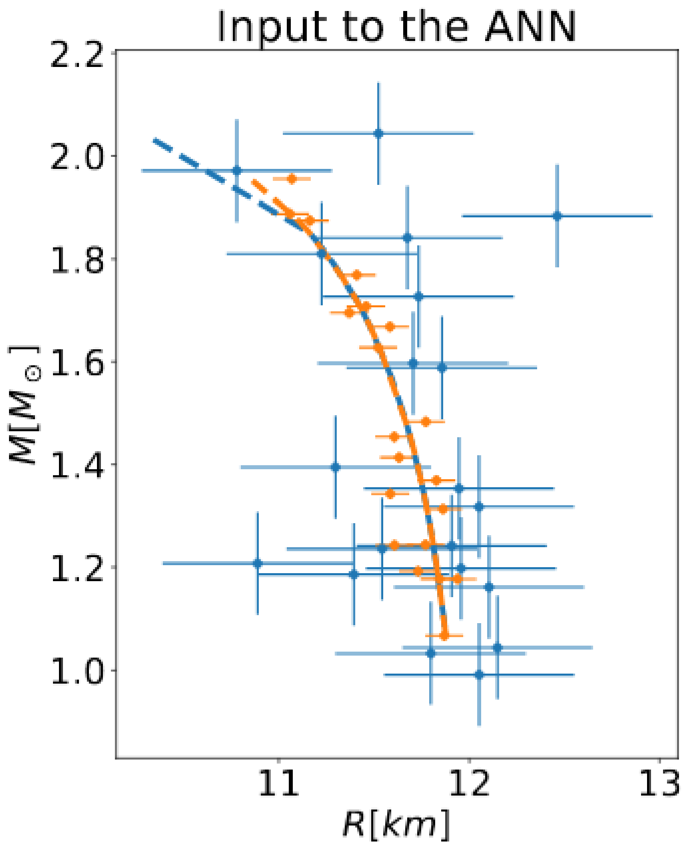

Uniform mass distribution
Double Gauss mass distribution
Mean Squared Error
10^{-3}
10^{-4}
10^{-5}
10^{-6}
10^{-7}
10
20
30
40
50
Number of observations
m_{err}: 0.00, $\hat{r}_{err}$: 0.00
m_{err}: 0.01, $\hat{r}_{err}$: 0.01
m_{err}: 0.01, $\hat{r}_{err}$: 0.10
m_{err}: 0.10, $\hat{r}_{err}$: 0.10
m_{err}: 0.10, $\hat{r}_{err}$: 0.50

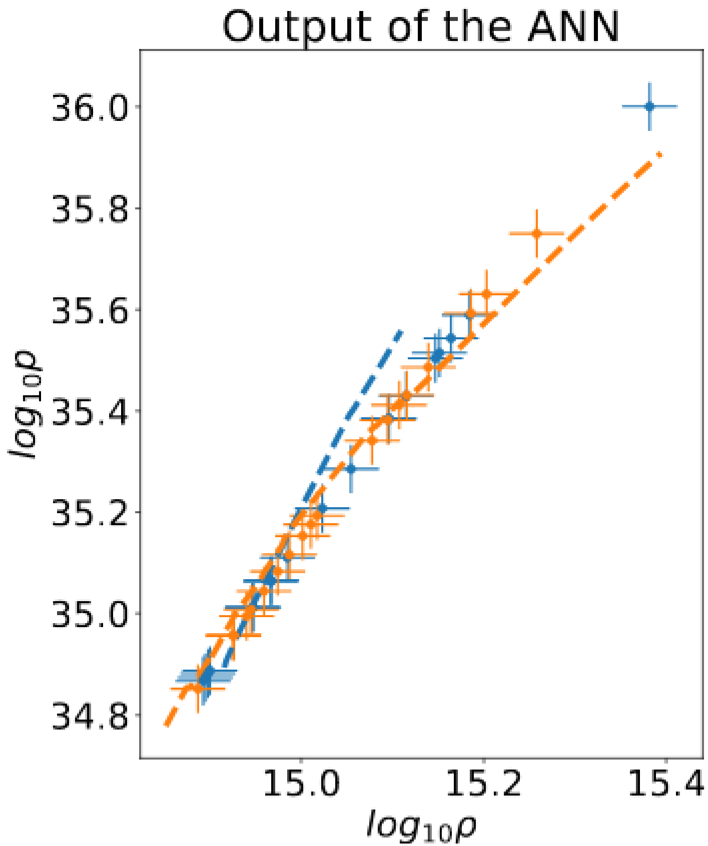
M(R̂) to R - reconstruction



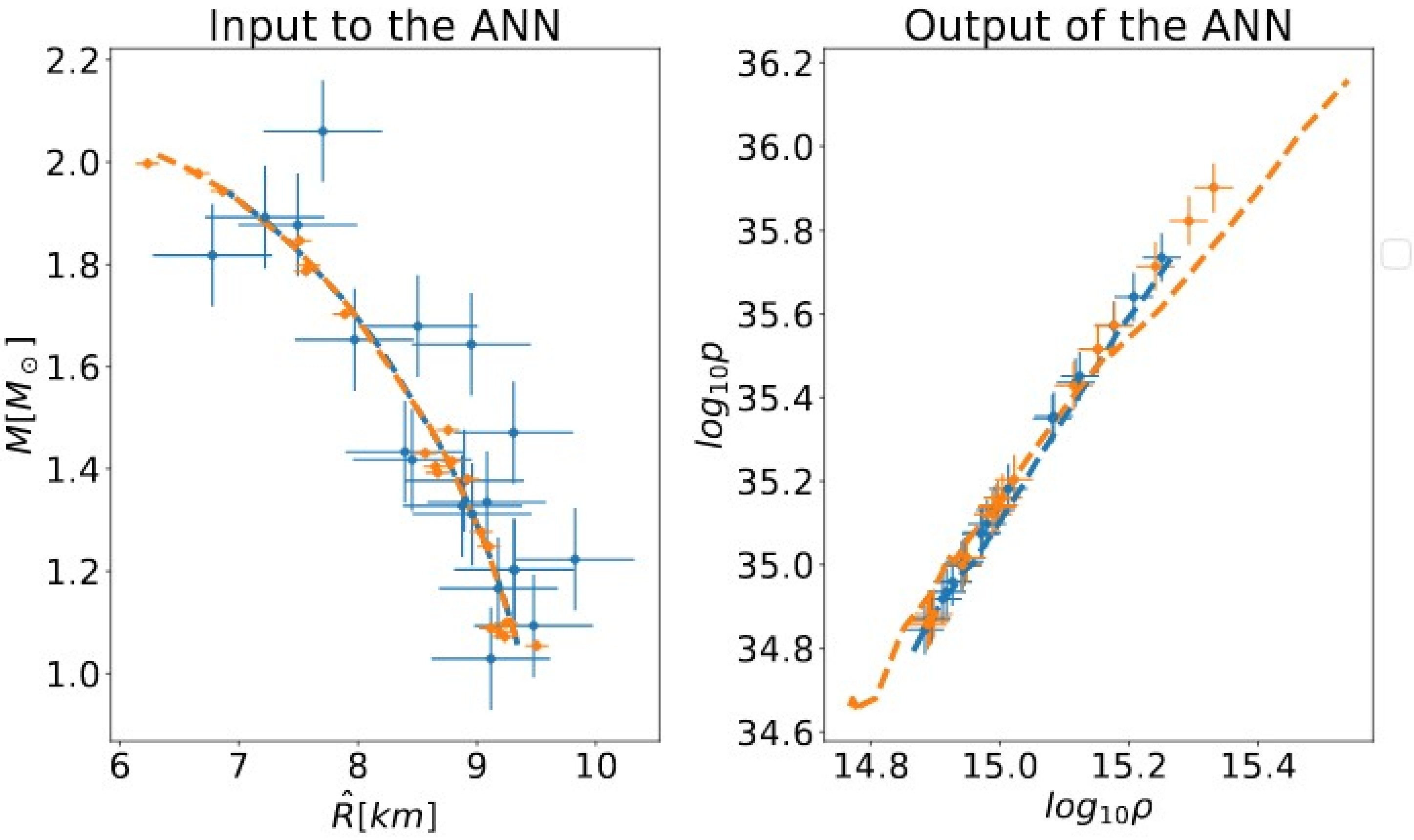
Real model - SLy4

Tests on Sly4 - M(R)





Tests on Sly4 - M($\hat{R}$)



Summary

- Our method allows to reconstruct EOS using both electromagnetic and gravitational observables in all considered cases
- Reconstruction of realistic EOS – Sly4 needs further work
- Will using both M(R) and M($\hat{R}$) allow to achieve better reconstruction?