CAMK - JC May 31st, 2021

Analyzing the Galactic pulsar distribution with machine learning

arXiv:2101.06145

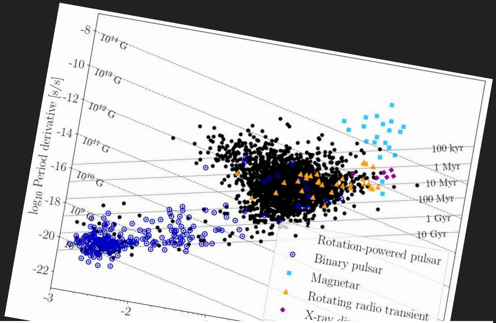
Dr. Vanessa Graber (graber@ice.csic.es)

in collaboration with Michele Ronchi, Albert Garcia Garcia, José Pons and Nanda Rea

Background

- We have detected **~2800 pulsars**, with **~2000** being **isolated**. They have diverse characteristics, visible in different parts of electromagnetic spectrum → **neutron star zoo**.

- We obtain more & better data, e.g., for ~400 objects **proper motions** are known (~200 for isolated ones).



$\beta_{\rm PSR}$, $n_{\rm e}$	PSRs	RRATs	XDINSs	Magnetars	Total	CCSN rate
FK06, NE2001	2.8 ± 0.5	$5.6^{+4.3}_{-3.3}$	2.1 ± 1.0	$0.3^{+1.2}_{-0.2}$	$10.8^{+7.0}_{-5.0}$	1.9 ± 1.1
L+06, NE2001	1.4 ± 0.2	$2.8^{+1.6}_{-1.6}$	2.1 ± 1.0	$0.3^{+1.2}_{-0.2}$	$6.6^{+4.0}_{-3.0}$	1.9 ± 1.1
L+06, TC93	1.1 ± 0.2	$2.2^{+1.7}_{-1.3}$	2.1 ± 1.0	$0.3^{+1.2}_{-0.2}$	$5.7^{+4.1}_{-2.7}$	1.9 ± 1.1
V+04, NE2001	1.6 ± 0.3	$3.2^{+2.5}_{-1.9}$	2.1 ± 1.0	$0.3^{+1.2}_{-0.2}$	$7.2^{+5.0}_{-3.4}$	1.9 ± 1.1
V+04, TC93	1.1 ± 0.2	$2.2^{+1.7}_{-1.3}$	2.1 ± 1.0	$0.3^{+1.2}_{-0.2}$	$5.7^{+4.1}_{-2.7}$	1.9 ± 1.1

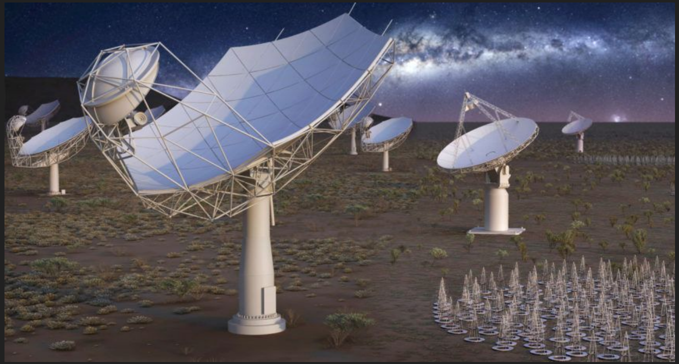
NS birth vs. galactic CCSN rates (Keane & Manchester 2008).

- **Galactic CCSN rate** insufficient for independent formation of different classes → evolutionary connection / metamorphosis?

Pulsar population synthesis

- We only observe a very **small fraction** of the **~10^9** neutron stars, expected to be present in the Milky Way.
- Instead of studying pulsars on an individual level, a popular approach has been / is to look at the **entire population:**
  - model birth properties with a **Monte-Carlo approach,**
  - **evolve parameters** forward in time,
  - compare mock sample to **observations** to constrain input.
- Provides information about birth rates, **initial distributions** of periods/kick velocities/magnetic fields/etc. → connected to stellar evolution, GRBs, FRBs, peculiar supernovae and more.

Motivation

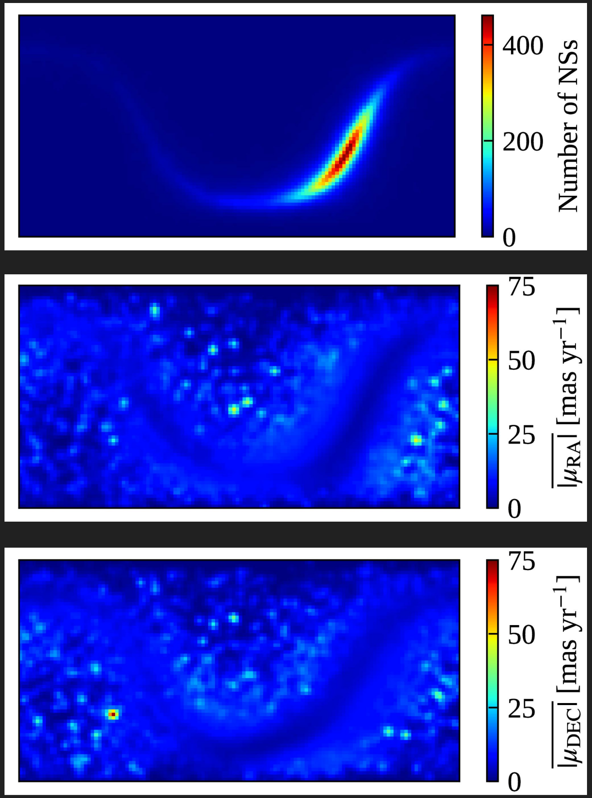


SKA Organisation

- Revisit the problem of population synthesis and specifically
    - look at / work towards new data
        - e.g. FAST / SKA / Athena.
    - improve on / use updated physical input
        - e.g. galactic model, e^- density model, emission physics.
    - model various NS classes consistently
        - combine observations in different wave bands.
    - use new computational techniques for parameter estimation
        - implement machine learning pipelines.

Dynamical evolution

- Focus on **positional & velocity evolution** and largely follow Faucher-Giguère & Kaspi (2006) with
  - spiral arm model of Yao et al. (2017) plus rigid rotation with T = 250 Myr.
  - galactic model of Marchetti et al. (2019).
  - exponential disk with scale height h_c.
  - single-component Maxwell kick-velocity distribution with dispersion σ_k.
- Evolve 10^5 stars for (up to) 10^7 yr until today, i.e., **birth rate** of 1 NS/century.

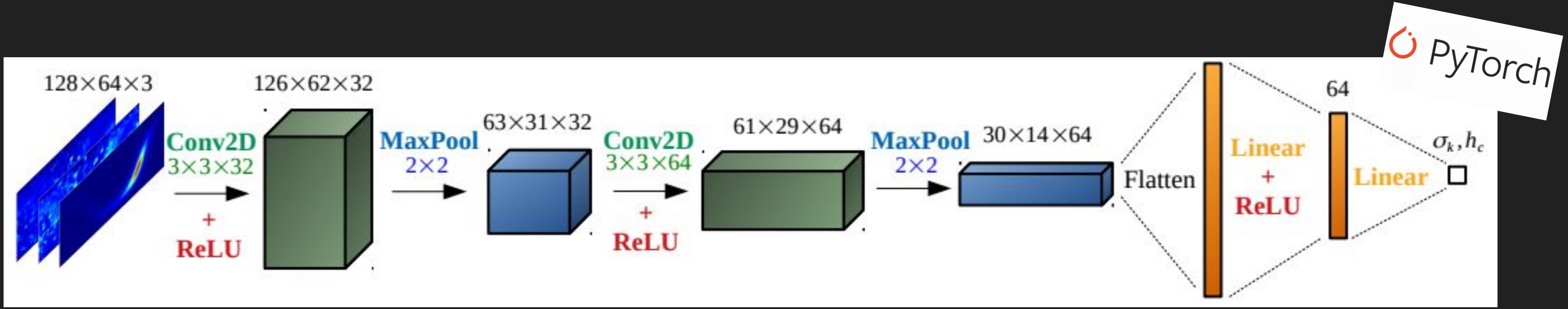


Stellar density & velocities in ICRS coordinates for fiducial values h = 0.18 kpc, σ = 265 km/s.

Machine learning framework

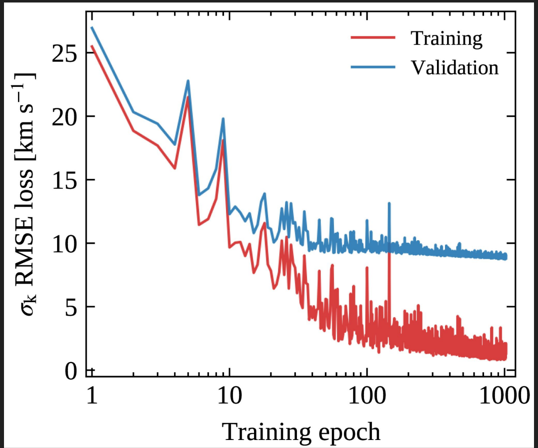
- Given input density & velocity maps, **predict parameters h_c and σ_k** that control the final pulsar population → use a **convolutional neural network** for this **regression problem.**

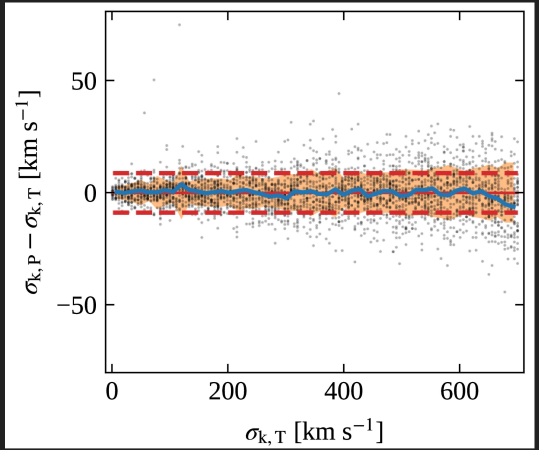
- We simulate populations by varying h_c and/or σ_k (labels) & then perform a range of **supervised learning** experiments varying, e.g., resolution, channels, architecture, and hyperparameters.

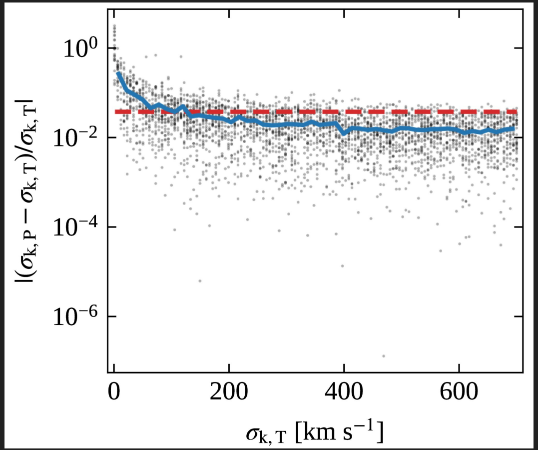


Training results

- With RMSE as loss function & validation metric, Kaiming initialisation & Adam for gradient-descent optimisation, we find for a data-set with 128 x 128 samples (80/20% training/valid. split):



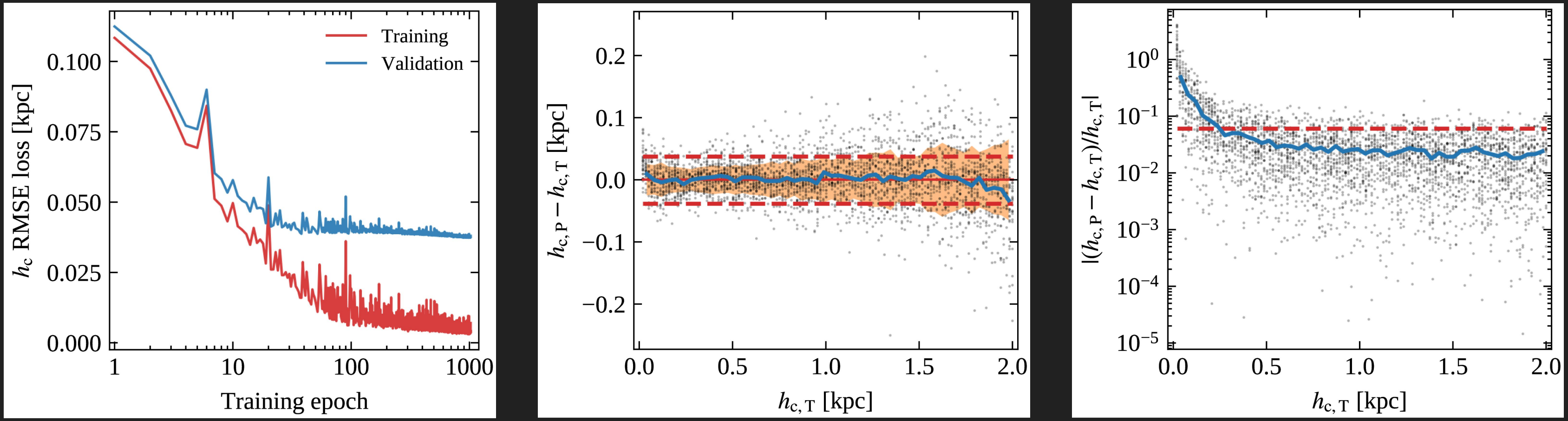




CNN validation results for σ_k in two-parameter experiment: RMSE = 8.8 km/s & MRE = 0.039.

Training results

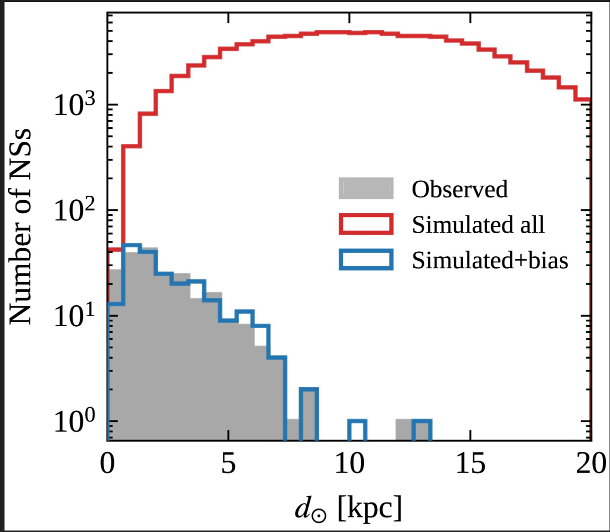
- With RMSE as loss function & validation metric, Kaiming initia-lisation & Adam for gradient-descent optimisation, we find for a data-set with 128 x 128 samples (80/20% training/valid. split):



CNN validation results for h_c in two-parameter experiment: RMSE = 0.038 kpc & MRE = 0.061.

Selection biases

- So far, our simplified approach has neglected selection effects and observational biases → use a **phenomenological approach** to analyse possible changes in network performance.

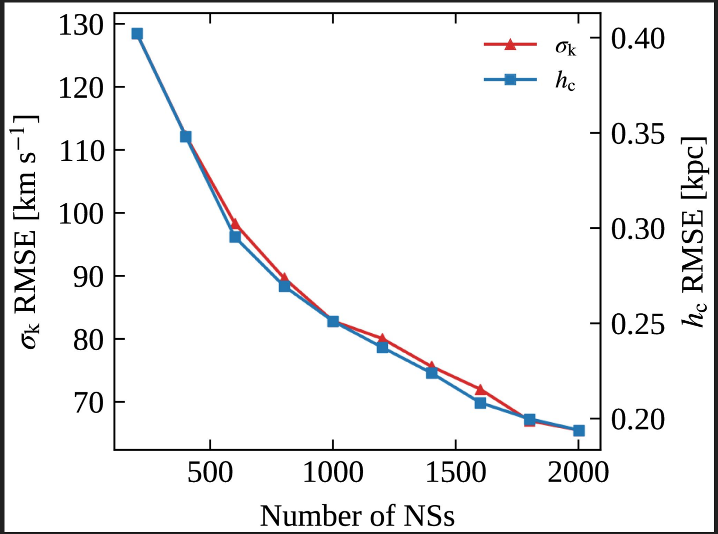


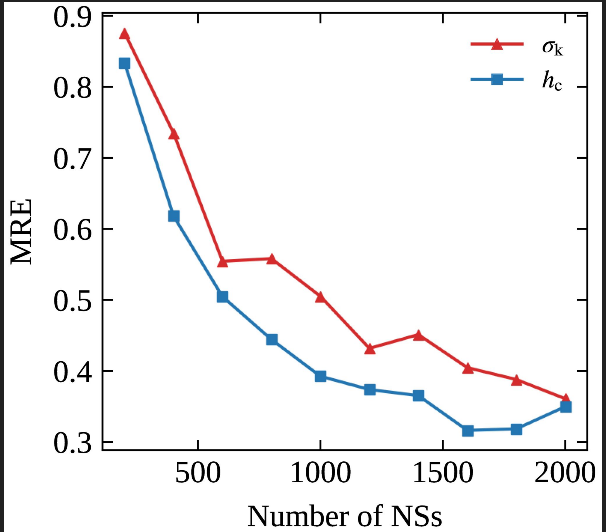
- Use proper motion and distance estimates for 216 isolated pulsars to deduce **empirical selection function** $f(d_\odot)$ and resample our fiducial population with $h_c = 0.18$ kpc and $\sigma_k = 265$ km/s using

$$f(d_\odot) = d_\odot^{-1} \exp(-d_\odot/2)$$

Resampled experiments

- Analyse the CNN's **predictive power** as a function of available data points (i.e. NSs) by resampling our fiducial simulation → accuracy strongly depends on observed number of objects.





Conclusions & outlook

- We studied possibility of using ML to reconstruct the dynamical birth properties from evolved pulsar populations → specifically focus on the **kick-velocity & scale-height distribution**.
- We find **absolute uncertainties** σ_k ~ 10 km/s & h ~ 0.05 kpc, and **relative uncertainties** of 0.01 for both → in realistic scenarios, these will be lower & strongly **limited** by **observations**.
- **Current** and **future directions** involve implementing
  - magnetorotational evolution (additional free parameters)
  - selection effects (emission, relevant surveys)
  - update our ML framework for multi-dimensional inference