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# A machine-learning based surrogate model of stellar evolution

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## Motivation

Many astrophysical studies require efficient but reliable stellar evolution models.
Examples:

- stellar parameter estimation based on iterative optimization techniques,
- rapid population synthesis and
- stellar *N*-body dynamics simulations.

However, for these, detailed stellar evolution modeling at scale using codes such as MESA is computationally too expensive!

## Methods

We construct a fast-to-evaluate surrogate model of stellar evolution based on detailed stellar evolution tracks pre-computed with the MESA code. These serve as training data for fitting a machine-learning (ML) model that not only replicates but generalizes MESA output over a quasi-continuous parameter space. The fitted model traces the evolution of stars from the zero-age-main-sequence (ZAMS) up to the end of core-helium burning over a ZAMS mass range of $0.6 \leq M_{\rm ini}/M_\odot \leq 300$, thereby covering > 99% of stellar lifetimes.

- **Data:** The MIST catalog (Choi et al. 2016)
- **Regression problem**:

$$\log\frac{L_i}{L_\odot}, \log\frac{T_{\rm eff,i}}{[\mathrm{K}]}, \log\frac{g_i}{[\mathrm{cm/s^2}]} \leftarrow f_{\rm ML}(\tau_i, M_{\rm ini}; Z = Z_\odot),$$

  where $L$ is the bolometric luminosity, $T_{\rm eff}$ the effective temperature, $g$ the surface gravity, $\tau$ the stellar age, $i$ the data index, $Z$ the metallicity (kept fixed) and $f_{\rm ML}$ the predictive model.
- **ML model**: A hyperparameter-optimized feedforward neural network (ffNN).

## Results I: Prediction of observables

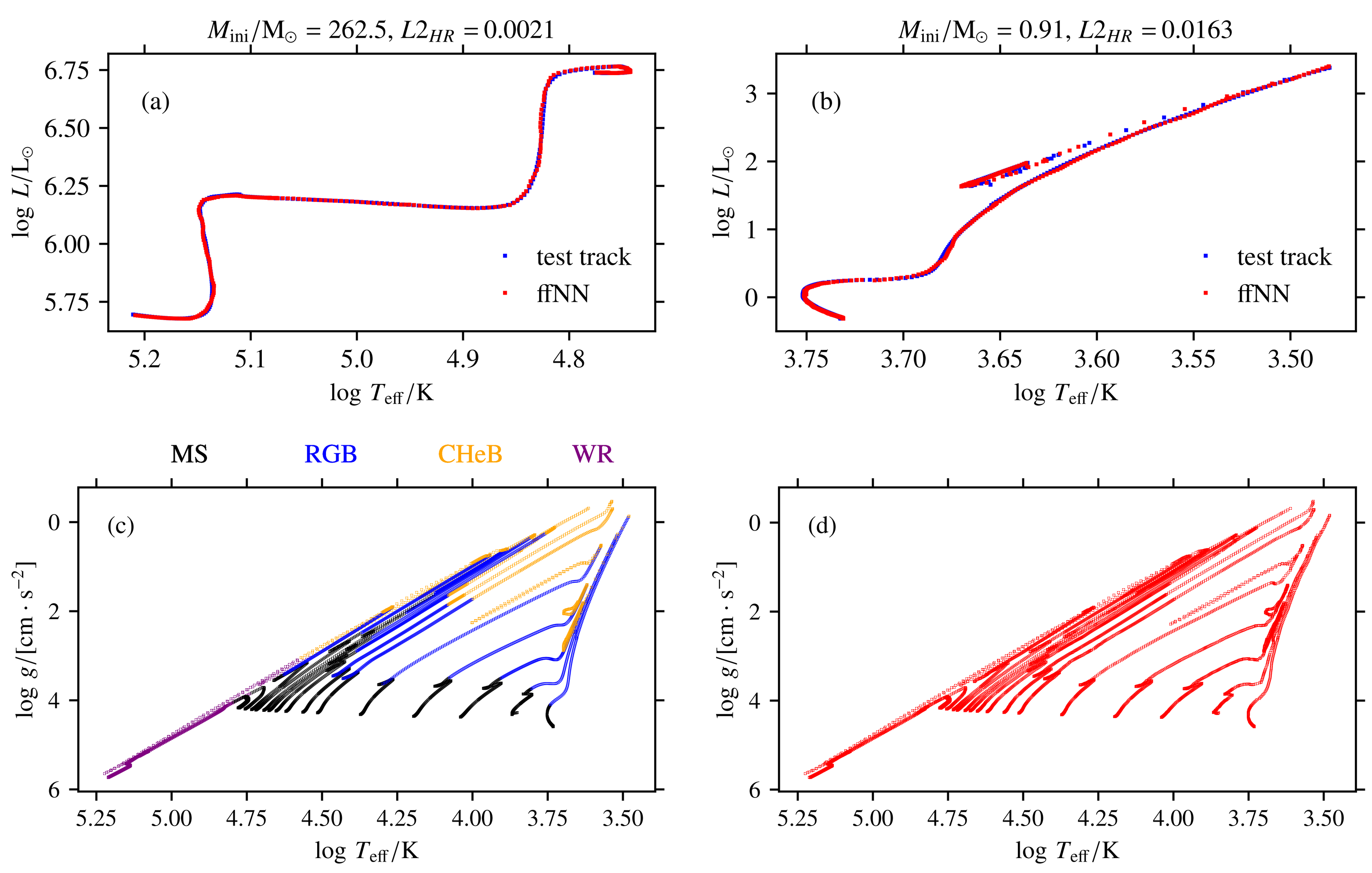


Fig. 1 upper pannels: The best (a) and the worst (b) prediction of a hold-out stellar evolution track in the Hertzsprung-Russell diagram at test ZAMS masses unseen by the ffNN model during training.
Fig. 1 lower panels: Comparison of the true (c) and the ffNN-predicted (d) stellar evolutionary tracks in the Kiel diagram over the entire set of test ZAMS masses unseen during training.

- **Accuracy:** mean prediction error is – depending on the predicted variable – 1-3 orders of magnitudes lower than typical observational uncertainties on $\log L/L_\odot$, $\log T_{\rm eff}/[\mathrm{K}]$ and $\log g/[\mathrm{g/cm^2}]$.
- **Efficiency:** The main advantage of the surrogate modeling is the speed-up – making $3 \cdot 10^6$ point predictions takes ∼45 seconds on a 4-core CPU!

## Results II: Prediction of isochrones

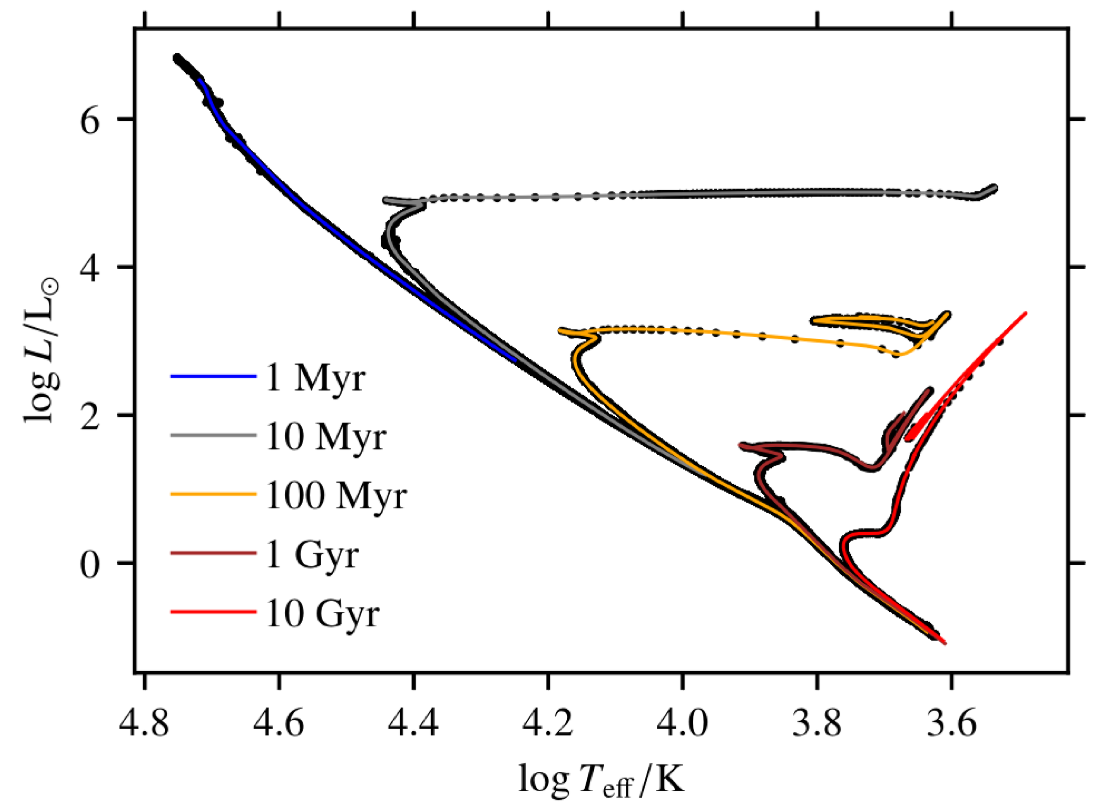


Fig. 2: Comparison of MIST isochrones with the surrogate-model predictions of stellar observables at fixed ages. The initial mass range $0.6 \leq M_{\rm ini}/M_\odot \leq 300$ is sampled over a log scale with a step size $\delta \log M_{\rm ini}/M_\odot = 5 \cdot 10^{-5}$ to obtain the parameter space points at which discrete predictions are made over a set of isochrone values (1 Myr, ..., 10 Gyr). The theoretical MIST isochrones are color-marked, while the ML-based point predictions are scatter-plotted in black.

- **The timescale-adapted evolutionary coordinate:** To reduce timescale variability of observables across orders of magnitude separated scales (e.g., evolution on the MS vs. through the Hertzsprung gap), we define analytically a latent variable, $s$, and use it instead of $\tau$ to model at significantly higher accuracy the evolution of stars.
- **Validation of the two-step predictive pipeline:** To map out

$$s_i \leftarrow (\tau_i, M_{\rm ini}; Z = Z_\odot),$$

  we train another supervised learning model, a $k$-nearest neighbors (KNN) regressor. For the prediction of isochrones, first, the KNN regressor predicts $s$ for given $\tau_i$ and $M_{\rm ini}$, and second, the ffNN-model uses $s_i$ and $M_{\rm ini}$ to predict the observables.

## Possible applications

The pre-trained ML models can be used e.g. to

- infer the ZAMS mass of a $Z = Z_\odot$ star,
- infer the age of a $Z = Z_\odot$ star,
- infer the age of a $Z = Z_\odot$ stellar cluster,
- infer the Initial Mass Function of a $Z = Z_\odot$ stellar cluster or
- test the Choi et al. (2016) stellar evolution model based on a $Z = Z_\odot$ population observation,

when the classical photometric observables $\log L$, $\log T_{\rm eff}$ and $\log g$ are given.

## Paper & open-source code

- **Paper:** Maltsev et al. (2024)
- **Code:** Zenodo-release containing a Jupyter Notebook that loads the pre-trained ML models and shows how to use them.

## Interested in applying the models? - Get in touch!

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- **Talk to me at EAS!**