# Modeling and Predicting the Dynamics of Globular Clusters with Deep Learning

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# Outline

Problem setting

Proposed pipeline

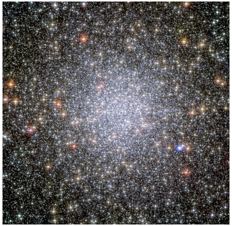
Towards more realistic modeling

# Problem setting

# Globular clusters

Fundamental and extreme stellar systems.

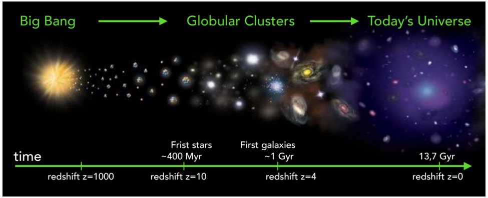
- Very common: our galaxy, the Milky Way, hosts 160 of them.
- Very dense: about $10^6$ stars per cluster.
- Very old: $13$ Gyr, comparable to the age of the Universe.



Credit: NASA, ESA, and the Hubble Heritage (STScI/AURA)-ESA/Hubble Collaboration

Fossils of the ancient universe

- High-redshift era.
- Assembly of galaxies.
- Earliest star formation.



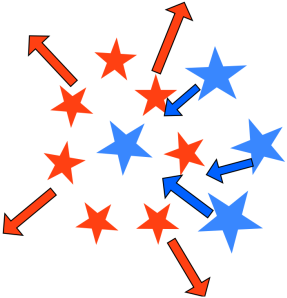
# Challenges

Open question of their origin.

- ▷ What are GCs properties today, e.g., mass, distance, age, number of black holes?
- ▷ How did they form in the primordial universe (initial properties)?
- ▷ What are the details of their evolution?

GC dynamics governed by many complex phenomena.

- ▷ Internal dynamics, e.g., star-by-star gravitational interaction.
- ▷ Influence of the host galaxy, e.g., formation of tails.
- ▷ Imprint of their initial formation process, including dark matter.
- ▷ over 13+ Gyr evolution.



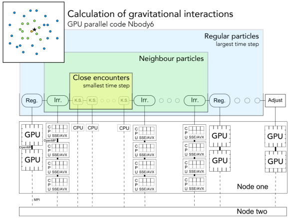
# N-body simulations

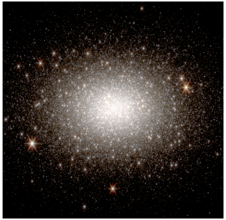
Direct approach for stellar dynamics.

- ▷ Highly accurate, physically principled.
- ▷ Star-by-star interactions modelled directly.
- ▷ Naturally account for dynamical / stellar evolution, e.g., mass segregation, mass loss, presence of black holes.
- ▷ Optimized code/hardware, e.g., GPU parallel code Nbody6++GPU.

☹ Costly simulations

- ▷ $10^6$ stars over 13 Gyr: $400+$ days of wall-clock time.
- ▷ Equivalent footprint of $\approx 9$ CO2 tons.

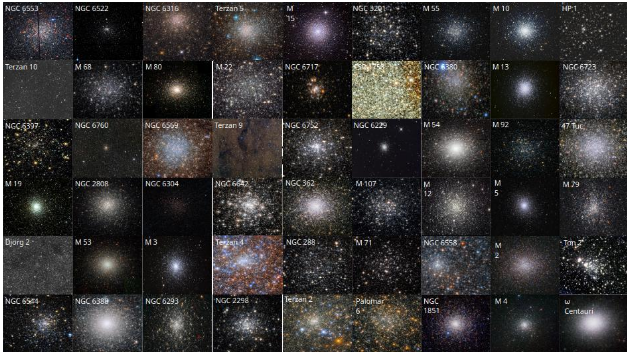


Wang et al., "nbody6++gpu: ready for the gravitational million-body problem", *Monthly Notices of the Royal Astronomical Society*, Vol. 450, Issue 4, pp. 4070-4080, May 2015.

# Context

- ▷ Modern astronomy programs generate a huge amount of data.
  - ▷ Vera C. Rubin obsservatory $\approx 20$ Tb/day.
- ▷ Need for efficient and sustainable methods to automatically process it.
  - ▷ N-body simulations are not appropriate for modeling individual GCs.

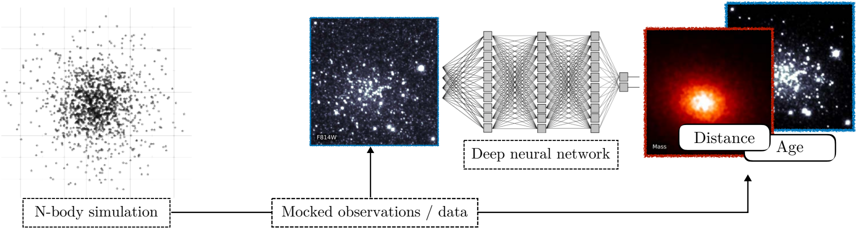



Compilation by Giulia Pagnini (ObAS)

# Proposed strategy

Bring together simulation-based and deep learning-based modeling.

- ▷ Leverage a reduced set of N-body simulations.
- ▷ Create realistic *mocked* observations of GCs.
- ▷ Design and train a neural network that predict the mass distribution, distance, and age.

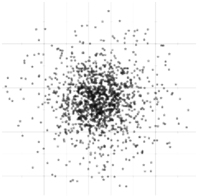


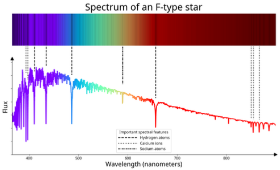
# Proposed pipeline

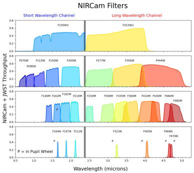
# From simulations to “observations”

From a simulation snapshot, compute:

- Stellar spectra: Get stellar parameters for each star, and generate spectra via, e.g., FSPS.
- Stellar magnitudes: Convolve spectra with the telescope filters to get the luminosity of a star in a given color range.
- Mocked observations: Convolve magnitude with the point spread function (PSF) to account for the telescope structure.





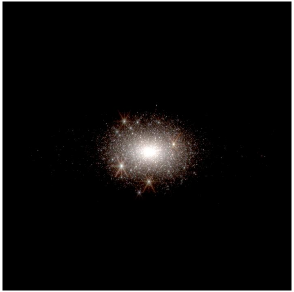

Conroy and Gun, “The Propagation of Uncertainties in Stellar Population Synthesis Modeling. III. Model Calibration, Comparison, and Evaluation”, *The Astrophysical Journal*, Vol. 712, Issue 2, pp. 833-857, April 2010.

# Snapshots at a fixed age

Mocked observations of N-body simulations using a JWST setup:

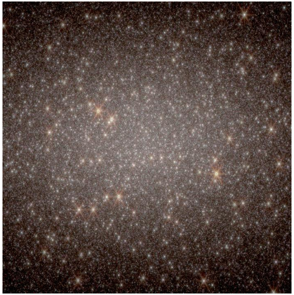
- Color images made with filters F070W, F115W, F356W.
- FoV 2 x 2 arcmin, pixel scale 0.06 arcsec

Distance = 800 kpc



Distance = 200 kpc

Distance = 20 kpc

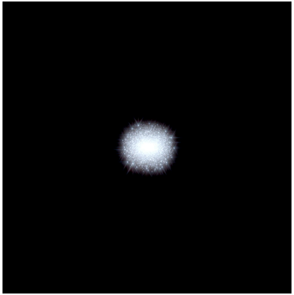


# Snapshots at a fixed distance

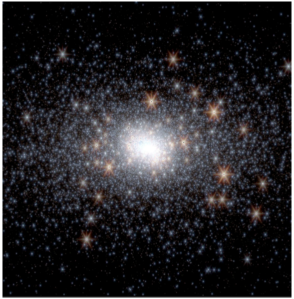
Mocked observations of N-body simulations using a JWST setup:

- Color images made with filters F070W, F115W, F356W.
- FoV 2 x 2 arcmin, pixel scale 0.06 arcsec

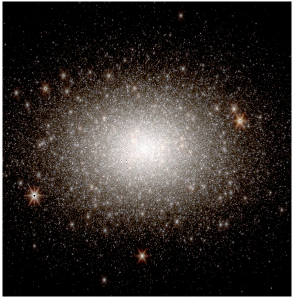
Age = 0 Gyr



Age = 0.1 Gyr



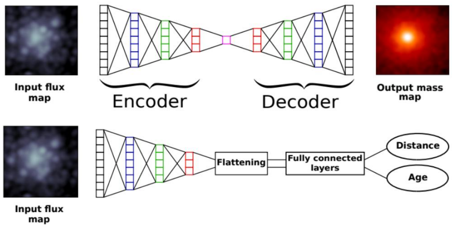
Age = 12 Gyr



# Original neural network model

## $\pi$-doc

- A convolutional encoder-decoder (CED) that predicts the mass distribution.
- A convolutional neural network (CNN) that predicts the distance and age.




## Training

- Extract 10k snapshots from 2 N-body simulations each = 20k training samples.
- Minimize the mean square error for each network.

## Test data

- Synthetic data: 8k samples extracted from another N-body simulation.
- Real data: 17 GCs from the Milky Way (MW).

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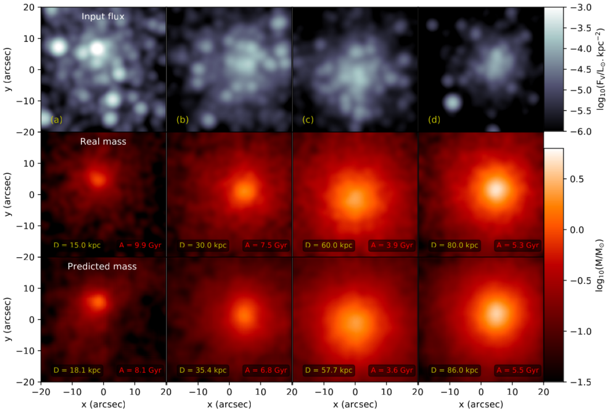
Chardin and Bianchini, "Predicting images for the dynamics of stellar clusters ($\pi$-DOC): a deep learning framework to predict mass, distance, and age of globular clusters", *Monthly Notices of the Royal Astronomical Society*, Vol. 504, Issue 4, pp. 5656-5670, March 2021.

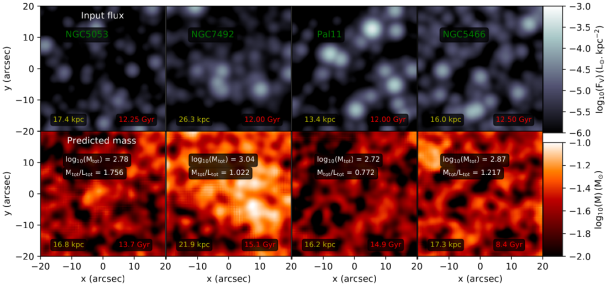
# Results on synthetic data

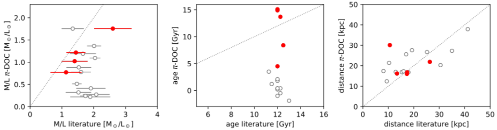



Average errors (test set):

- ▷ Pixel-by-pixel mass prediction: 27%
- ▷ Total mass in a FoV: 15%
- ▷ Total M/L: 11%
- ▷ Age: 1.5 Gyr
- ▷ Distance: 6 kpc

# Results on real data




Results are consistent with the literature for small GCs.

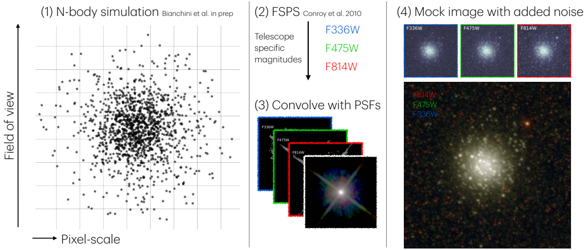
## Limitations

- ▷ Most real GCs are larger than in the simulation setup (about $10^4$ stars).
- ▷ MW clusters are not representative of all GCs.
- ▷ $\pi$-doc processes clean ($=$ noise-free) images, and uses one color channel.

# Towards more realistic modeling

# Improving data generation

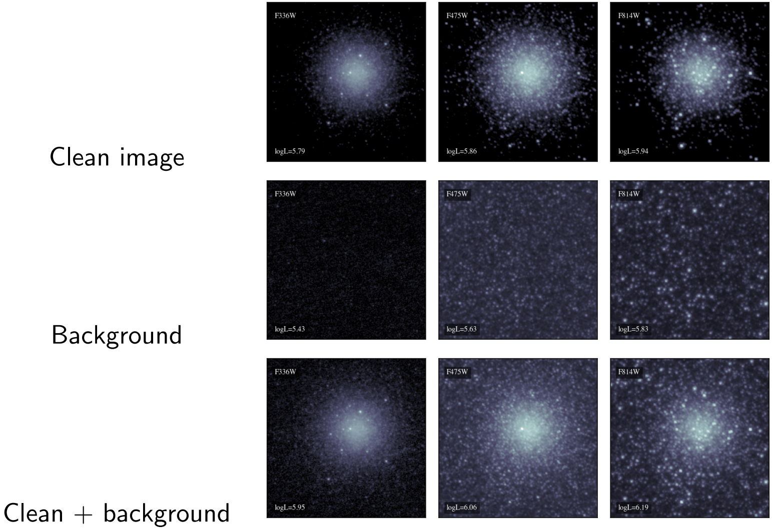
- More N-body simulations $(20)$, larger number of stars $(10^6)$.
- Account for 3 filter / color channels (F336W, F475W, F814W) + PSF from the HST.
- Include two types of noise:
  - Poisson noise: simulates instrument / measurement noise.
  - Galactic noise: simulates the impact of the surrounding galaxy.



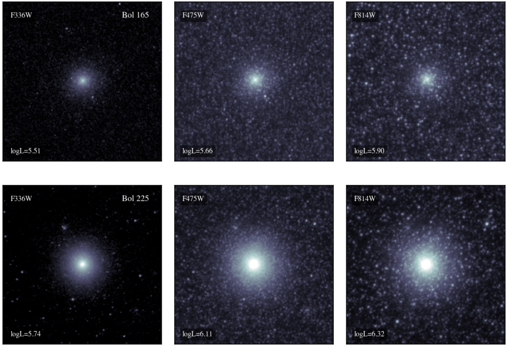

Noise = extinction-corrected images from Andromeda (HST PHAT survey).

Bianchini, "ROLLIN': Rotating Globular Clusters simulations. I. The kinematic evolution of realistic direct N-body models", *under review in Astronomy & Astrophysic*, 2025.

# New mocked observations



# Real observations

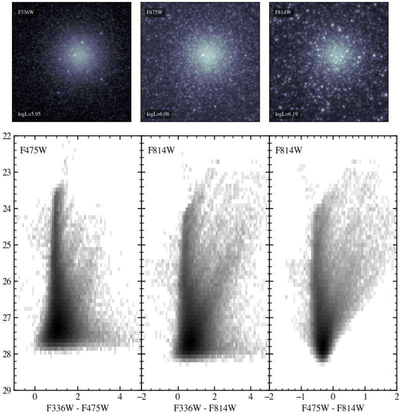



Bol165

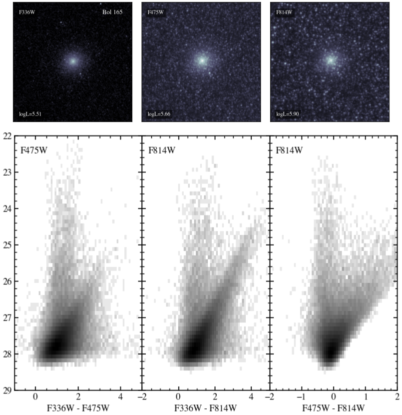
Bol225

# Mocked vs. Real

## Mocked




## Bol165

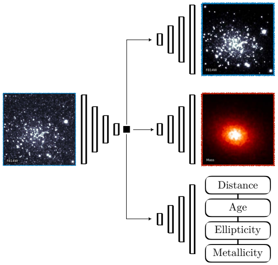


# Improving the model

$\pi$-doc has been merged into one single network.

## Multiple outputs

- ▷ Mass prediction.
- ▷ Image denoising / decontamination.
- ▷ Age and distance.
- ▷ Metallicity.
- ▷ Ellipticity / axis angle.




## Multiple inputs

- ▷ One magnitude (log-flux: F814W) + two *colors* (diff. between magnitudes: F336W-F814W and F475W-F814W) + 3 color magnitude diagrams (CMDs).
- ▷ CMDs are beneficial for predicting distance / age, but not helpful for predicting the mass / clean GC (= they do not contain spatial information).

# Training

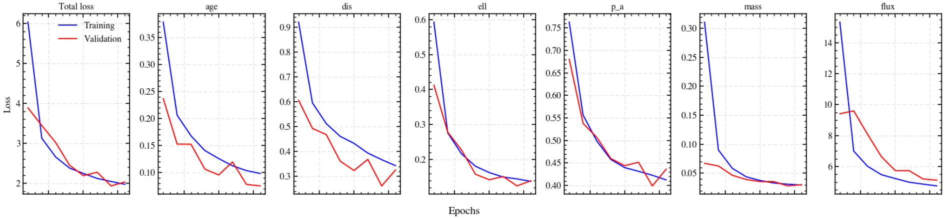
Dataset with $200$k samples.

- $\approx 120$k training, $\approx 40$k validation, and $\approx 40$k test (from different simulations).
- Real test data: about $300$ GC images from the Andromeda galaxy.

Loss function $=$ sum of task-specific terms: $\sum_i \lambda_i \times ||\text{output}_i - \hat{\text{output}}_i||^2$.

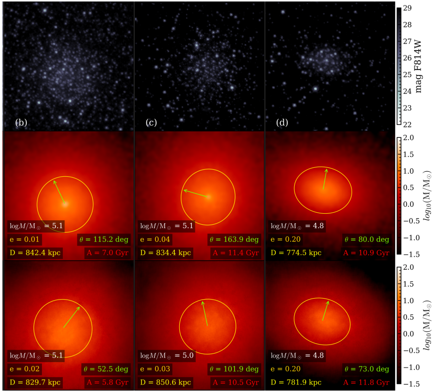
- $\lambda_i = 1$, $\forall i$ except for the denoising branch ($= 0.2$).

Training log (8 epochs, 3 days)

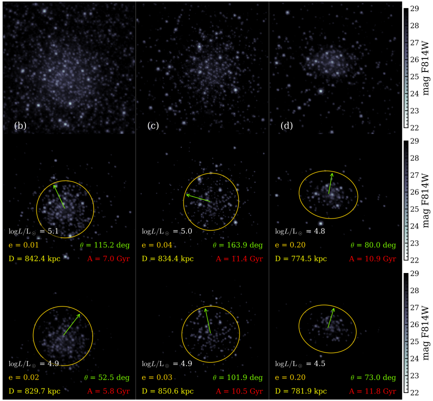


# Results on synthetic data

Mass prediction

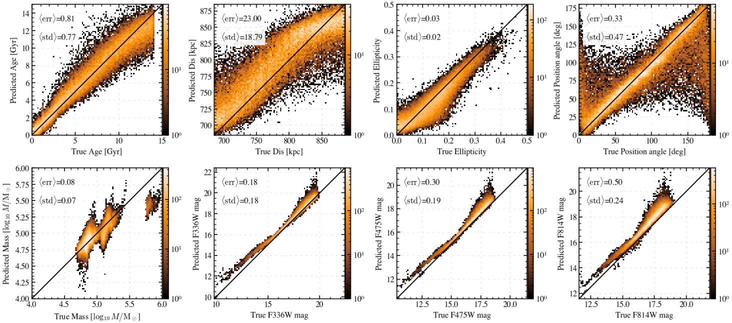



Denoising



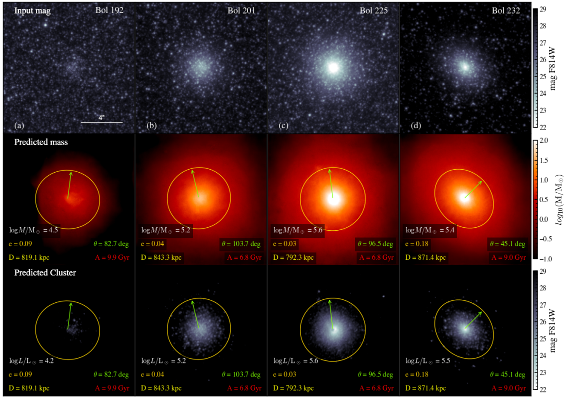

- Overall recovery of the mass distribution, but less accuracy at the outskirt.
- Denoised GCs are too faint, outskirt details are lost.

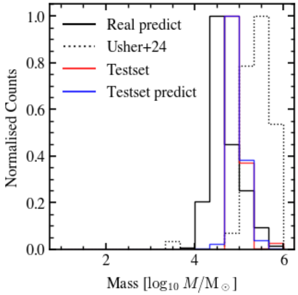
# Results on synthetic data - predicted vs. true




- ▷ Distance / age are overall well estimated, nothing too far out of range.
- ▷ Ellipcity values close to 0 are difficult to estimate accurately.
- ▷ Mass and luminosity are underestimated.

# Results on real data



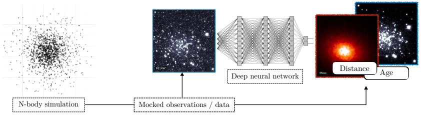




- ▷ Mass is underestimated; age / distance are consistent with the literature.
- ▷ Denoised GCs are still slightly too faint, since $\pi$-doc has not been trained on such bright clusters.
- ▷ Mocked images masses are bellow those of real GCs (according to litterature values): need to consider *denser* initial conditions.

# Conclusion

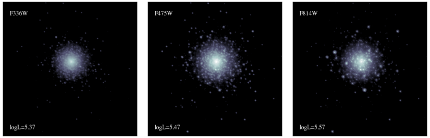
## Combining simulation-based and deep learning-based modeling of GCs

- ▷ A novel approach to learn the dynamics of GCs.
- ▷ Promising results on simulated data.
- ▷ Consistent results with the litterature on low-mass / low-density clusters.




## Future work

- ▷ Include a new set of more dense simulations.
- ▷ Fine-tune architecture / training process.
- ▷ Adaption of the algorithm to more general cases, e.g., other telescopes, galaxies. . .



# Thanks!

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https://magronp.github.io/

https://github.com/magronp/