Galaxy Cluster Mass Estimation Using Deep Learning

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Introduction

Dynamical mass estimators are a class of cluster measurements which leverage information from spectroscopic observations of kinematics of member galaxies in order to infer cluster masses. While theoretically sound, vanilla applications of dynamical methods produce significant biases and scatter in realistic cluster mass predictions, owing to drastic departures from the idealistic assumptions for which the theory holds. Gravitational instabilities and member galaxy selection effects are prime examples of complex systematics which violate theory assumptions and introduce error into mass estimates.

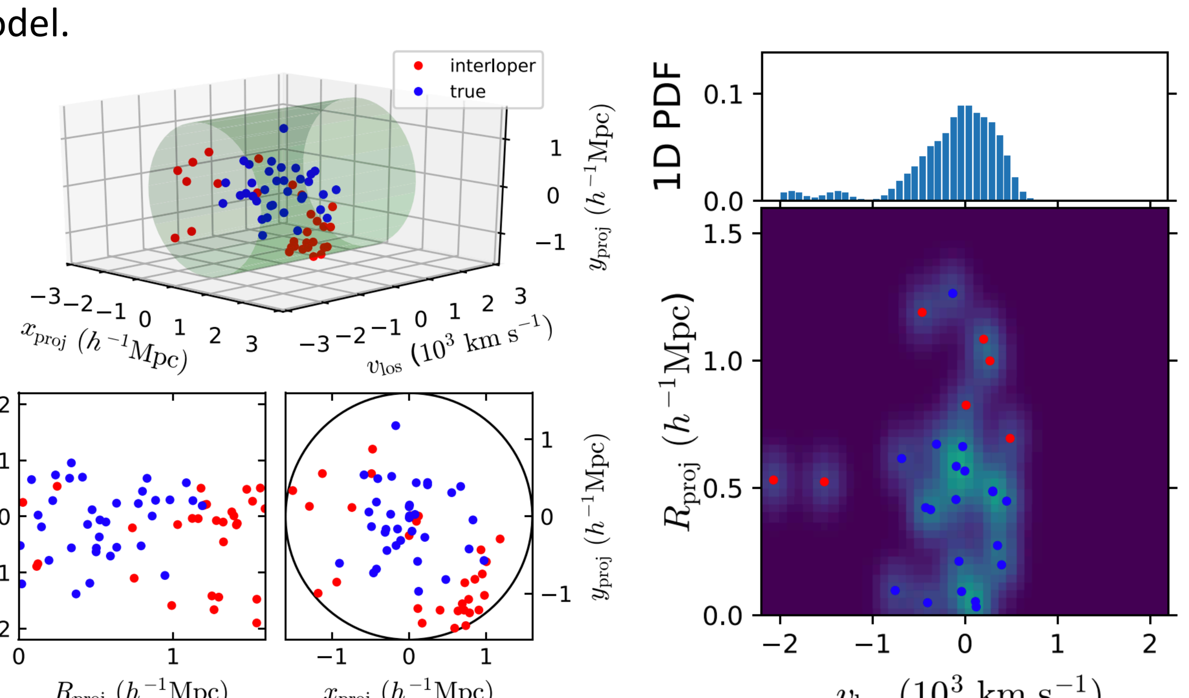
Mass estimates of the Coma cluster (right) motivated Fritz Zwicky to make the first inference of dark matter in 1933.

Dataset

We train and test our model on a catalog of realistic mock observations of clusters derived from large volume cosmological simulations (Planck MDPL2, Uchuu). Simulated clusters are converted to realistic mock observables in agreement with the simulation's original cosmology. Mock cluster observations are designed to include realistic systematics which would impact dynamical mass estimates, including physical effects (cluster mergers, triaxiality) and selection effects (interlopers).

Pre-processing

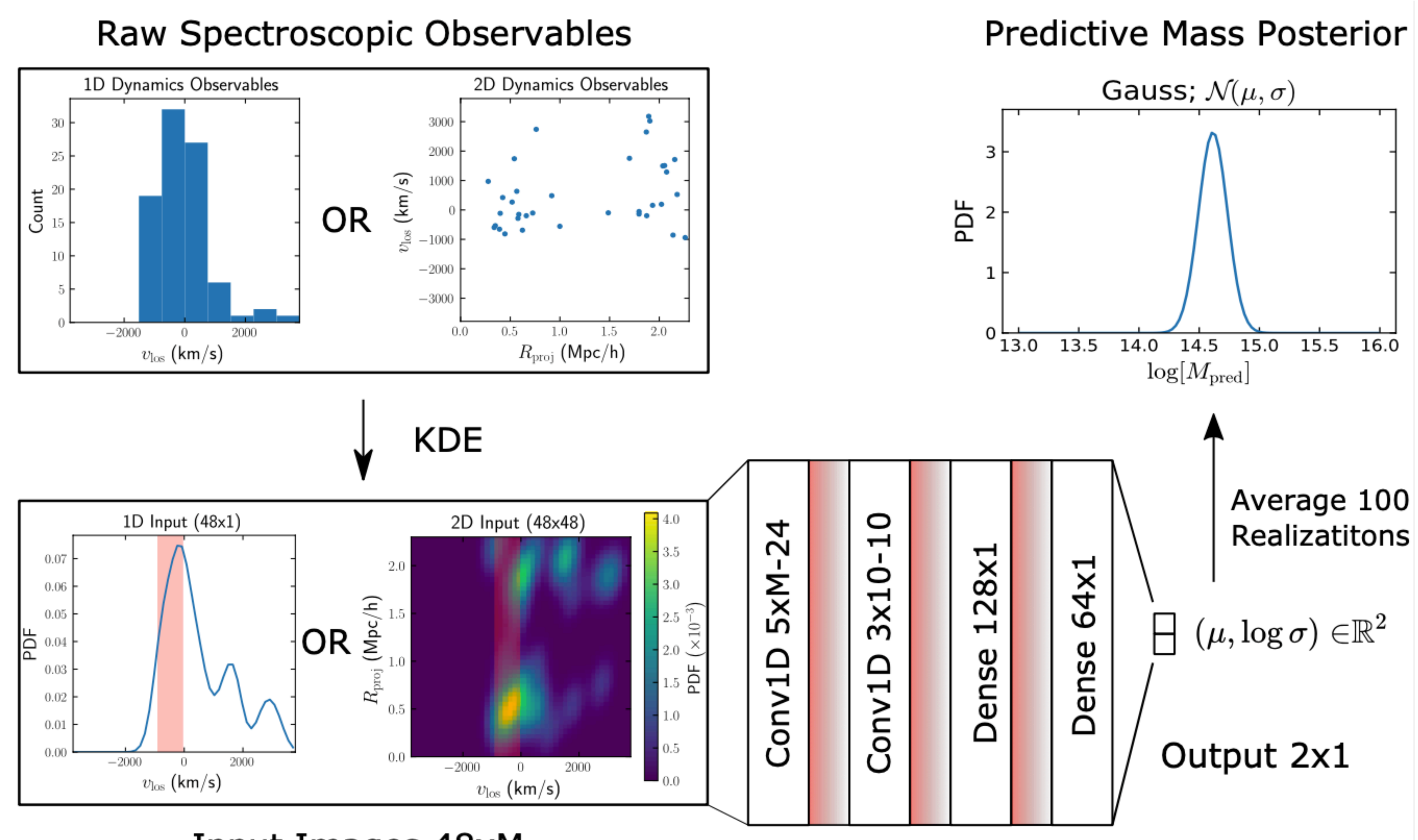
For each cluster, we map the distribution of member galaxies in projected phase space using a KDE PDF mappings generated with KDEs can sufficiently encapsulate features of the underlying member distribution while remaining relatively invariant to variations in the sampling rate. These mappings serve as direct input to our ML model.



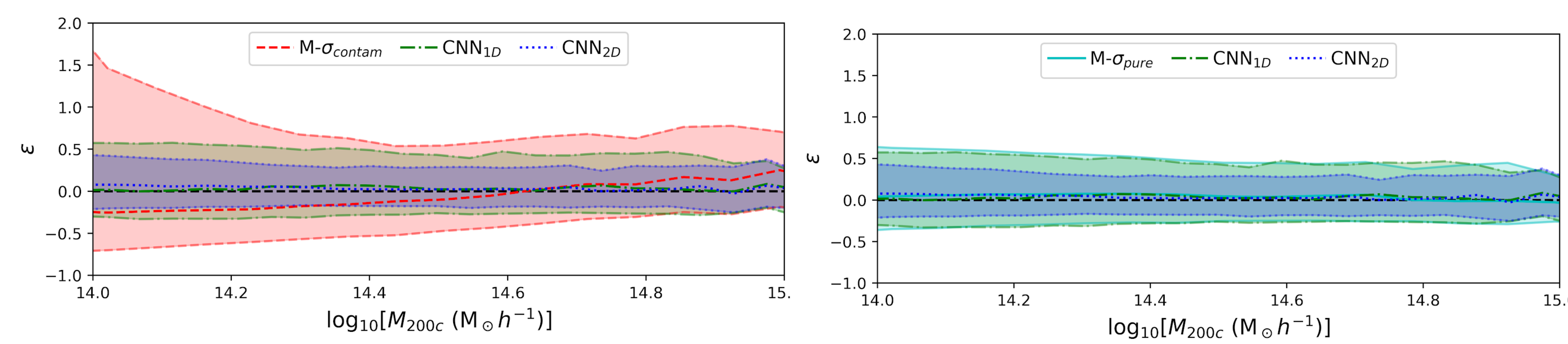
Model

To appropriately model spatially-separated systematic effects, we train a CNN model to learn the relationship between dynamical observables to cluster mass. We study the impact of including various sets of dynamical observables in model inputs (e.g. 1D: {v_{los}} or 2D: {v_{los}, R_{proj}}).

In Ho et al. 2019, we design and test a simple point mass estimator. In Ho et al. 2021, we extend this model using Approximate Bayesian Dropout marginalization, to accurately recover full mass posteriors. In both cases, we cross-validate our model on catalogs of simulated clusters.



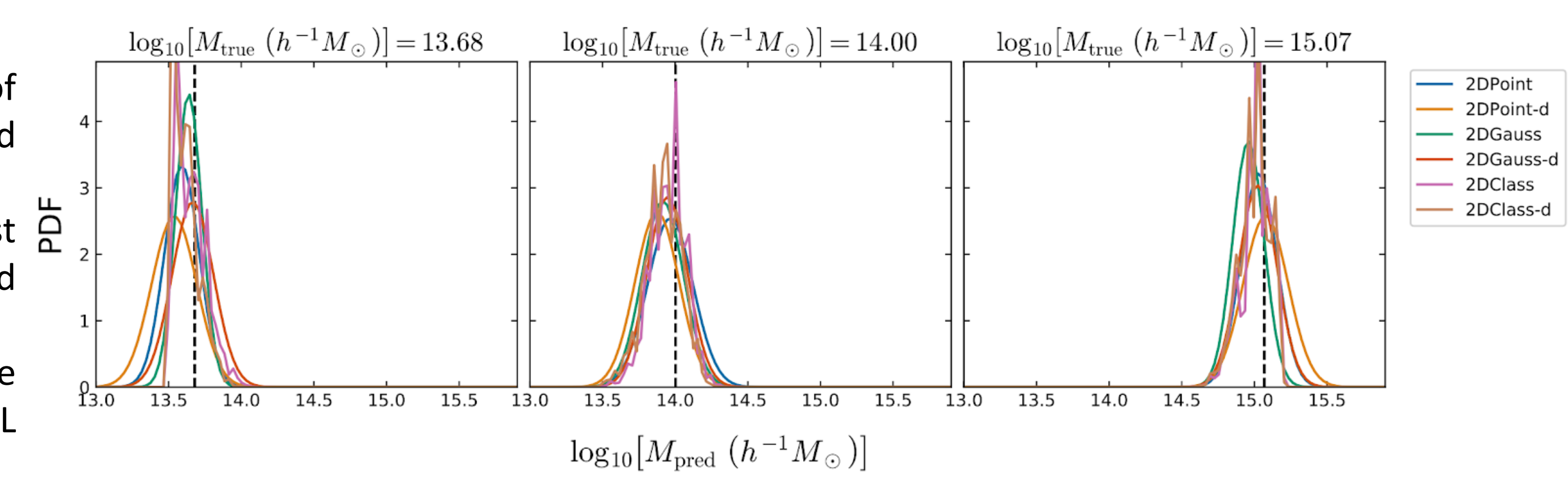
Results



Prediction residuals for deep learning point mass estimators versus simple and ideal M-sigma estimators.

In Ho et al. 2019, we showed that:

- CNN models reduced empirical scatter of simple M-σ masses by a factor of 2.5 and ideal M-σ masses by 30%.
- CNN models were considerably more robust to variations in data richness than M-σ and other ML approaches.
- CNN models reduced training and inference time by 30x when compared to other ML approaches.



Recovered mass posteriors for simulated clusters using various deep learning models.

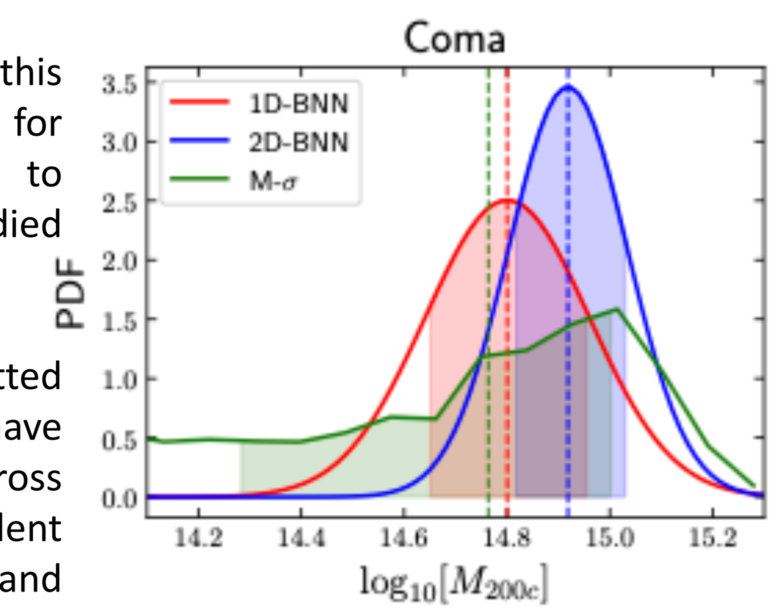
In Ho et al. 2021, we showed that:

- We are able to recover mass posteriors of simulated clusters which are roughly-Gaussian and statistically consistent with true mass.
- Model posteriors are well calibrated for mid-range mass clusters. The best performing models can recover within +/- 1% of 64 and 90 percentile confidence intervals.
- Slight biases exist for very high/low mass clusters at the edges of our training set.
- Epistemic uncertainties don't necessarily improve our posterior calibration.

Observational Extensions

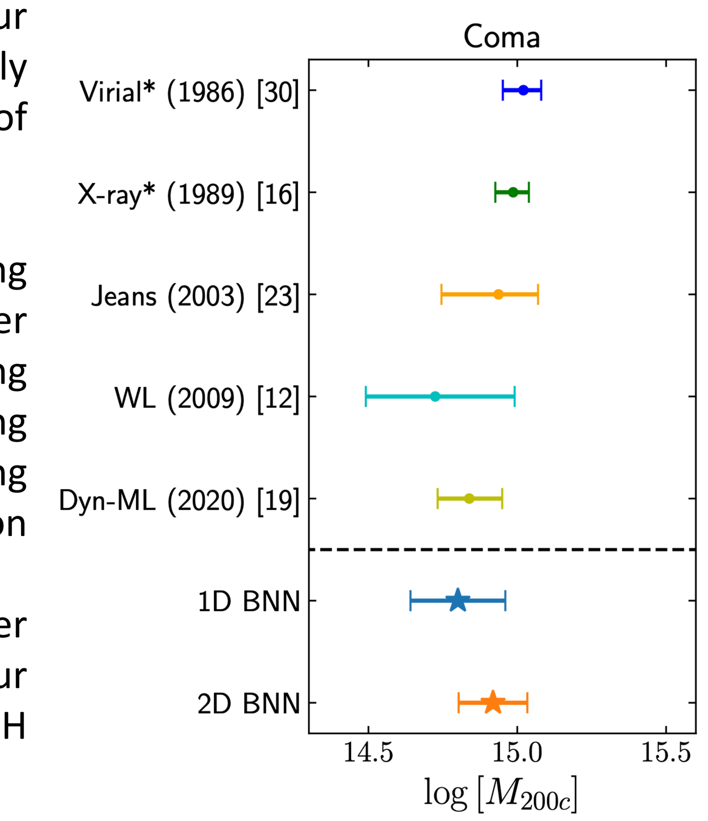
The next step in validating this model and preparing it for large-scale surveys is to evaluate it on well-studied observational systems.

In a paper recently submitted to *Nature Astronomy*, we have validated this model across multiple independent cosmological simulations and extended our predictions to the famous Coma cluster. Our results show that our predictions are highly consistent with other probes of Coma's mass.



Our posterior predictions of Coma mass versus the standard M-σ model.

We are working on extending these methods to further observational systems using sets of more realistic training simulations. In an upcoming paper, we train our models on photometrically-selected samples of mock cluster observables and extend our prediction to the CLASH clusters.



Our mass predictions of the Coma cluster relative to historical measurements.

Conclusion

- We introduced an image-recognition based model for calculating cluster masses from galaxy dynamics (Ho et al. 2019) which reduced scatter of traditional methods by ~2.5x
- We applied methods for measuring uncertainties from deep learning models (Ho et al. 2020)
- We extended these models to observational data from real systems such as the Coma (submitted to Nature Astronomy) and CLASH clusters (in prep)

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