Inferring the Dark Matter halo mass in galaxies from other observables with Machine Learning

MACHINE LEARNING FOR ASTROPHYSICS
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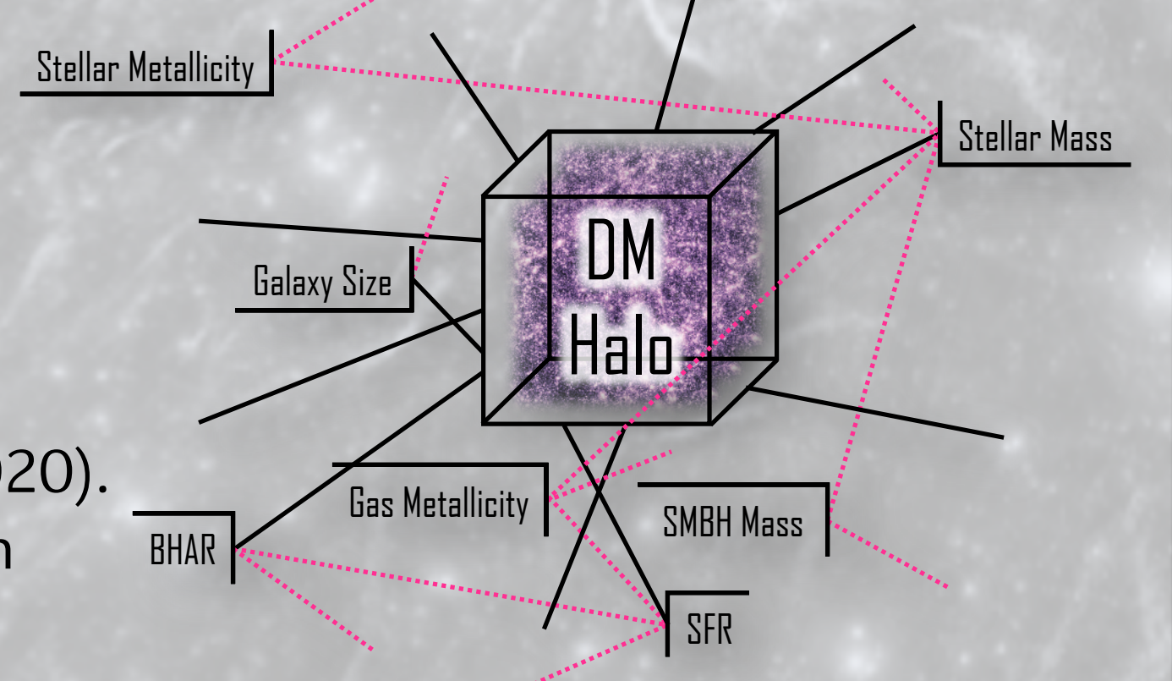
Abstract

In the context of the galaxy-halo connection, it is widely known that the dark matter (DM) halo of a galaxy exhibits correlations with other physical properties, like the well-studied stellar-to-halo-mass relation. However, given the complexity of the problem and the high number of galaxy properties that might be related to the DM halo in a galaxy, the study of the galaxy-halo connection can be approached relying on machine learning techniques to shed light on this intricate network of relations. Hence, with the aim of inferring the DM halo mass and then finding a unique functional form able to link the halo mass to other observables in real galaxies, in this poster I present some preliminary results of this project obtained by relying on the state-of-the-art Explainable Boosting Machine (EBM) algorithm, a novel method with a very high accuracy and intelligibility in the field of the generalised additive models with pairwise interactions (GA^{2}M). In this poster, I illustrate an analysis performed on a sample of galaxies at $z = 0$ extracted from the IllustrisTNG simulation, making use of several galactic properties. This method is proving to be very promising, finding, at all redshifts, a scatter of around 0.11 dex between the actual value of MDM from the simulation and the value predicted by the model.

Linking DM halos to other galactic properties

An important aspect to be investigated to link DM halos to their host galaxies concerns our knowledge on how the diverse galaxy properties correlate with their halos, as well as, how a given property can be a good estimator for the mass of DM halos. The idea behind the connection that should subsist between DM halo mass and other galaxy properties lies at the basis of galaxy formation and evolution theory. Indeed, this connection should find origin during the process of structure formation, when galaxies formed as the result of baryon condensation inside the gravitational wells yielded by DM halos (e.g. Rees & Ostriker, 1977; White & Rees, 1978; Fall & Efstathiou, 1980; Blumenthal et al., 1984). The entire process gives rise to the so-called *galaxy-halo connection*. As discussed in Wechsler & Tinker (2018), the existence of a relationship between the DM halo and its galaxy does not specify directly which galaxy properties are more linked to their halo, and in particular Which are the more useful to infer its mass. The most well-known relation between the DM halo and its host galaxy is the so-called stellar-to-halo mass relation (SHMR), that can be derived for example from galaxy formation models or parametrised models (e.g., Kravtsov et al., 2004; Moster et al., 2010; Leauthaud et al., 2011; Wechsler & Tinker, 2018; Behroozi et al., 2019). Together with possible primary properties directly linked to DM halos, we have to bear in mind that they show, in turn, other relations with other quantities. An example is given by the stellar mass which exhibits several further correlations: for example, the M_*–M_{BH} relation (e.g., Magorrian et al., 1998; Reines & Volonteri, 2015), or the relations with the stellar and gas metallicities (e.g., Tremonti et al., 2004; Gallazzi et al., 2005, 2006; Mannucci et al., 2010; Mingozzi et al., 2020). Hence, because of the complexity of the problem and the high number of features that might be related to the DM halo in a galaxy, the study of the galaxy-halo connection can be performed exploiting ML methods to shed light in this intricate network of possible relations among several galaxy properties.



Generalized Additive Models & GA²Ms

A Generalized additive model (GAM, Hastie & Tibshirani, 1990) is an additive model whose ability is to capture the role of the predictive features exploiting a series of smooth functions. Let assume a *training dataset* $D = \{(x_i, y_i)\}_1^N$, where N is the size of the dataset, $x_i = (x_{i1}, \dots, x_{ip})$ denotes a feature vector composed by p features, and y_i is the target variable, that, in our case, would be the DM mass. With x_j we indicate the j-th variable within the space of features. The GAM formulation can be written as

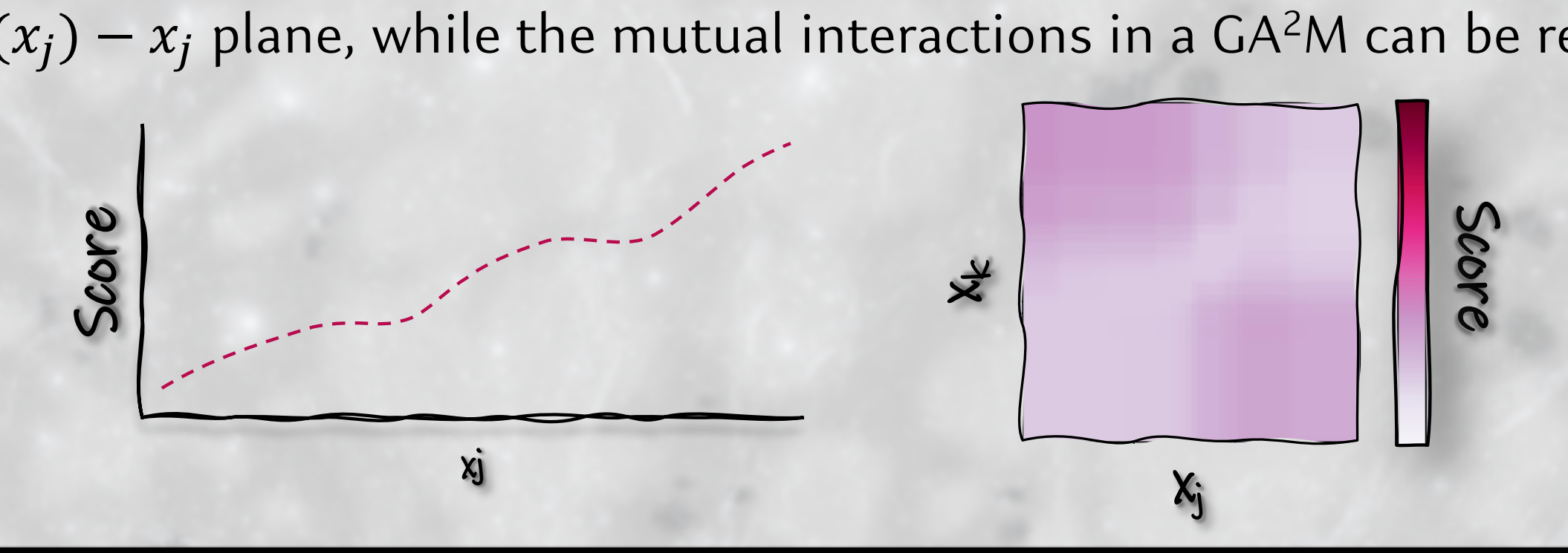
$$g(E\,[y]) = \beta_0 + \sum_j f_j(x_j) = \beta_0 + f_1(x_1) + \ldots + f_p(x_p)$$

where y is the dependent variable that we would like to estimate, $E[y]$ indicates the expected value, g is the so-called *link function*, and for each functional term f_j, called <u>*shape function*</u>, $E[f_j] = 0$. The functional terms f_j are *non-parametric functions* whose shapes are completely determined by the data.

In order to improve the accuracy of the model, we can add other terms to the standard GAM, for instance allowing for the presence of the pairwise interactions obtaining a ***<u>Generalized Additive Models with pairwise interactions</u>*** (Lou et al., 2013, Caruana et al., 2015, GA^{2}M):

$$g(E\,[y]) = \beta_0 + \sum_j f_j(x_j) + \sum_{j \neq k} f_{jk}(x_j, x_k)$$

The high intelligibility of GAMs and GA^{2}Ms lies in the straightforward visualisations of the feature terms: indeed, the relationship between each variable x_j and the corresponding function f_j in a GAM can be visualised in the $f_j(x_j) - x_j$ plane, while the mutual interactions in a GA^{2}M can be represented as maps of $f_{jk}(f_j, f_k)$.



An application to IllustrisTNG

Our scope is to understand the importance of some galactic features in the inference of DM mass in order to find a functional form useful to estimate the DM content in real galaxies.

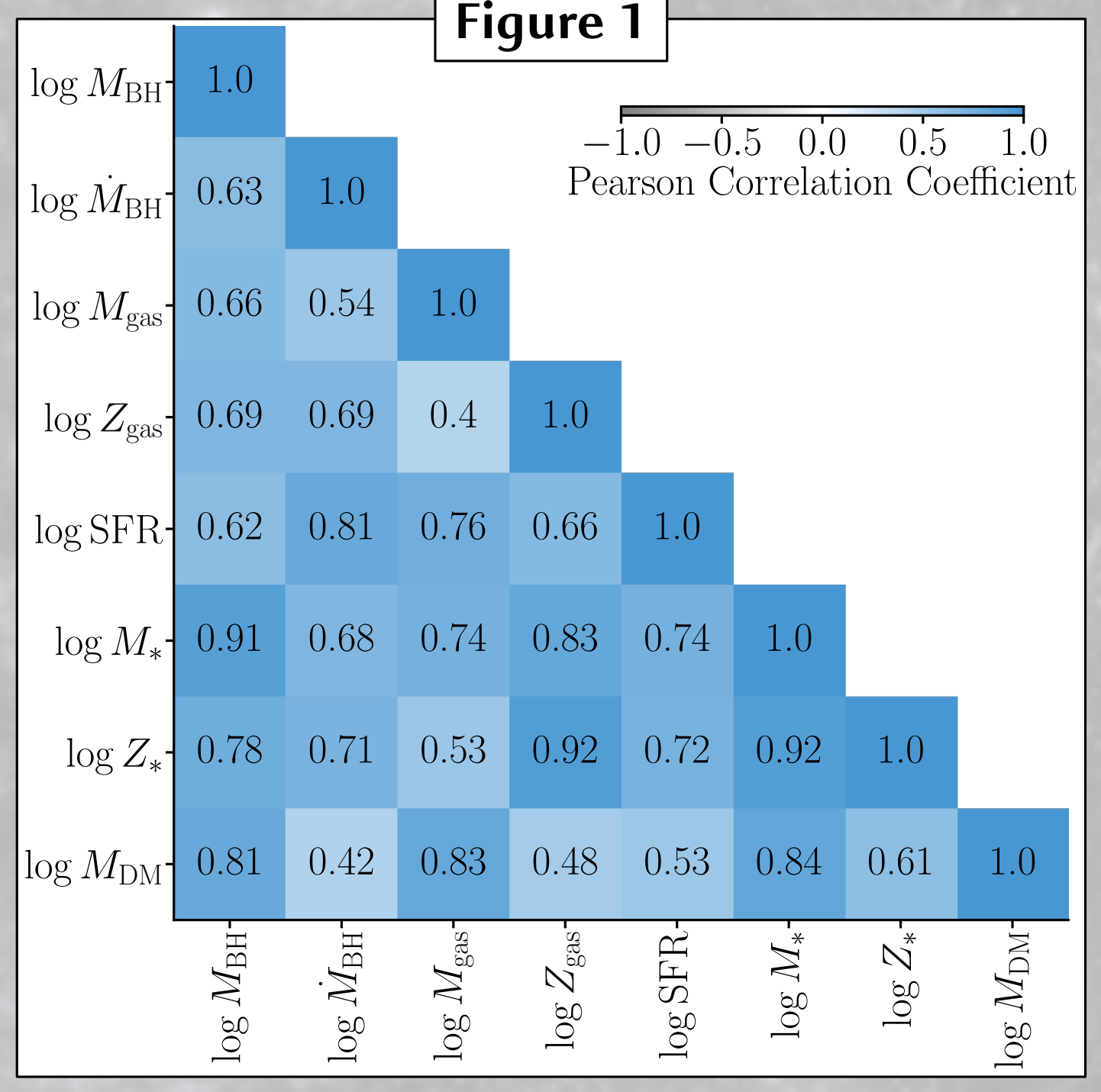
As a first application, we selected from the $z = 0$ snapshot of IllustrisTNG100-1 (Marinacci et al., 2018; Naiman et al., 2018; Nelson et al., 2018; Pillepich et al., 2018a; Springel et al., 2018) all subhalos. Our sample is composed of 31501 subhalos and we randomly split it into a ***<u>training sample</u>*** (22050 subhalos) and a ***<u>test sample</u>*** (9451 subhalos) with a ratio of 70:30. For each subhalo, together with the estimate of the DM mass M_{DM}, we take into account **<u>7 features</u>**:

- the stellar mass M_*;
- the gas mass M_{gas};
- the black hole mass M_{BH};
- the stellar metallicity Z_*;
- the gas metallicity Z_{gas};
- the black hole accretion rate $\dot{M}_{BH}$;
- the star formation rate SFR.

All these properties relate to the sum of all particles/cells within *twice* the stellar half mass radius

In **Figure 1**, the correlation matrix among all the properties of the subhalos of the training sample, showing the values of the Pearson Correlation Coefficient for each pairs

Figure 1



$\log M_{\rm BH}$	1.0							
$\log \dot{M}_{\rm BH}$	0.63	1.0						
$\log M_{\rm gas}$	0.66	0.54	1.0					
$\log Z_{\rm gas}$	0.69	0.69	0.4	1.0				
$\log {\rm SFR}$	0.62	0.81	0.76	0.66	1.0			
$\log M_*$	0.91	0.68	0.74	0.83	0.74	1.0		
$\log Z_*$	0.78	0.71	0.53	0.92	0.72	0.92	1.0	
$\log M_{\rm DM}$	0.81	0.42	0.83	0.48	0.53	0.84	0.61	1.0
	$\log M_{\rm BH}$	$\log \dot{M}_{\rm BH}$	$\log M_{\rm gas}$	$\log Z_{\rm gas}$	$\log {\rm SFR}$	$\log M_*$	$\log Z_*$	$\log M_{\rm DM}$

Training and testing the model

Microsoft Research released a state-of-the-art ML method called ***<u>Explainable Boosting Machine (EBM)</u>***, a C++/Python fast implementation of the GA^{2}M (Nori et al., 2019). To learn, EBM makes use of state-of-the-art ML techniques like *bagging* and *boosting*. The great advantage of EBM is that it is not only highly accurate, but being a complete *glassbox method*, it is also even more intelligible than a classic linear or logistic regression models. In this section, the fitting procedure of the training sample with the EBM regressor is described. In addition to the 7 features listed above, we consider also the <u>*three most relevant pairwise interactions*</u>. **Figure 2** shows the overall importance of the features and of the three most important pairwise interactions in making the inference of the DM mass. As clearly visible from the plot, each term is playing a role in inferring the DM mass, but the gas mass, the stellar mass and the black hole mass have a significantly stronger role. The length of each bar in **Figure 2** is obtained computing the mean of the absolute score for each term. When the model makes predictions, it will use each feature graph as a "look up table" to retrieve a score that the feature contributes to an individual prediction.

Figure 3 shows, as an example, the 1D shape function of the stellar mass. The y-axis indicates the score, i.e., the value in units of $\log(M_{DM}/M_\odot)$ to be added to a reference value, in this case $\log(M_{DM}/M_\odot) \simeq 10$. The shaded region along the shape profile (not clearly visible being very tight) represents the ±1 standard deviation of the variation of score estimated by 100 rounds of bagging. The vertical dashed line and the vertical shade area trace the median and the 68% of the distribution of the stellar mass in the training sample. Though the three baryonic components, i.e., the gas, stellar, and BH masses, are crucial for the prediction of DM mass, explaining the detailed behaviour of each score profile is not so trivial and needs a deep-dive analysis of single subhalos in the target sample. An example of this argument is the *hump-like structure* in the stellar mass score profile at around $\log(M_{DM}/M_\odot) > 10.8$. A possible explanation may be found in the role of mergers in these massive galaxies, whose stellar mass growth is mainly dominated by the accretion of ex-situ stellar populations, as found in Pillepich et al. (2018a), Tacchella et al. (2019), and <u>*Cannarozzo et al, submitted to MNRAS*</u> (stay tuned!).

Finally, in **Figure 4**, a comparison between the DM masses directly drawn from the simulation (M_{true}) and those predicted by the model (M_{pred}) for the subhalos in the test sample is illustrated, while **Figure 5** shows the distribution of the difference between these quantities: this distribution is tight with a scatter of about 0.11 dex, that reduces even to around 0.05 dex when subhalos with a total mass (i.e., meaning by total mass the sum of the masses of all particles and cells of all components in each subhalo) $\log(M_{tot}/M_\odot) > 11$ of are considered.

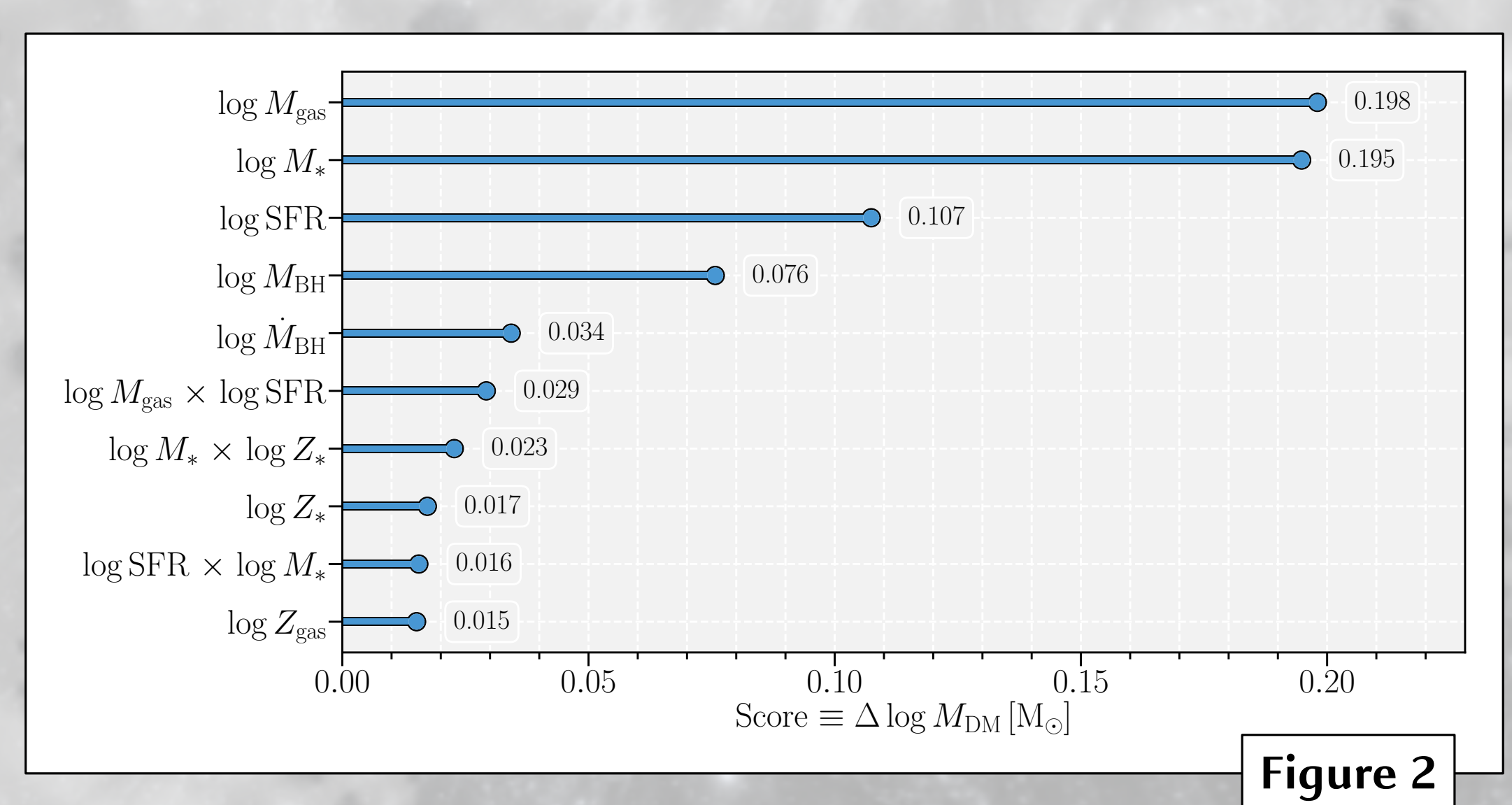


Figure 2

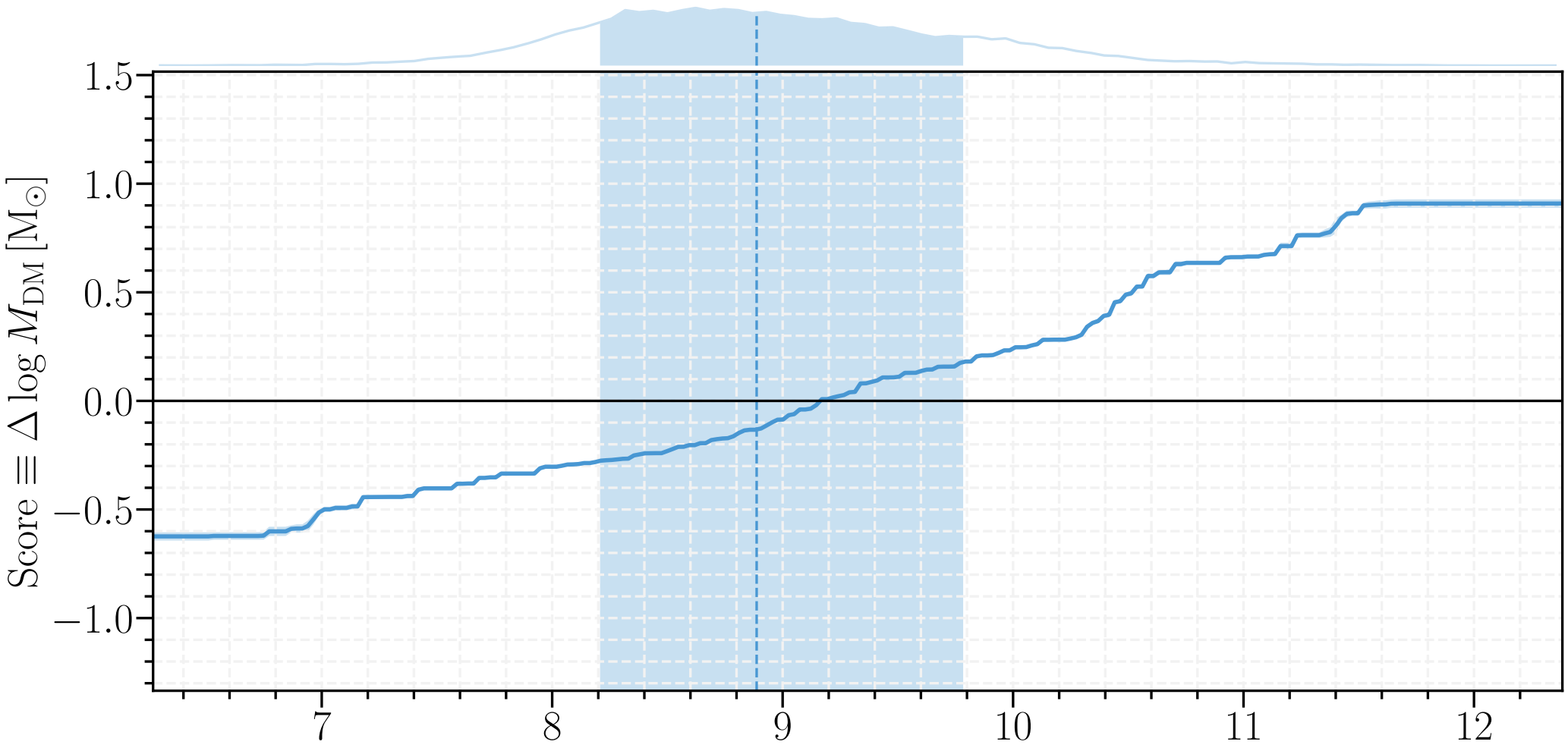


Figure 3

Figure 4

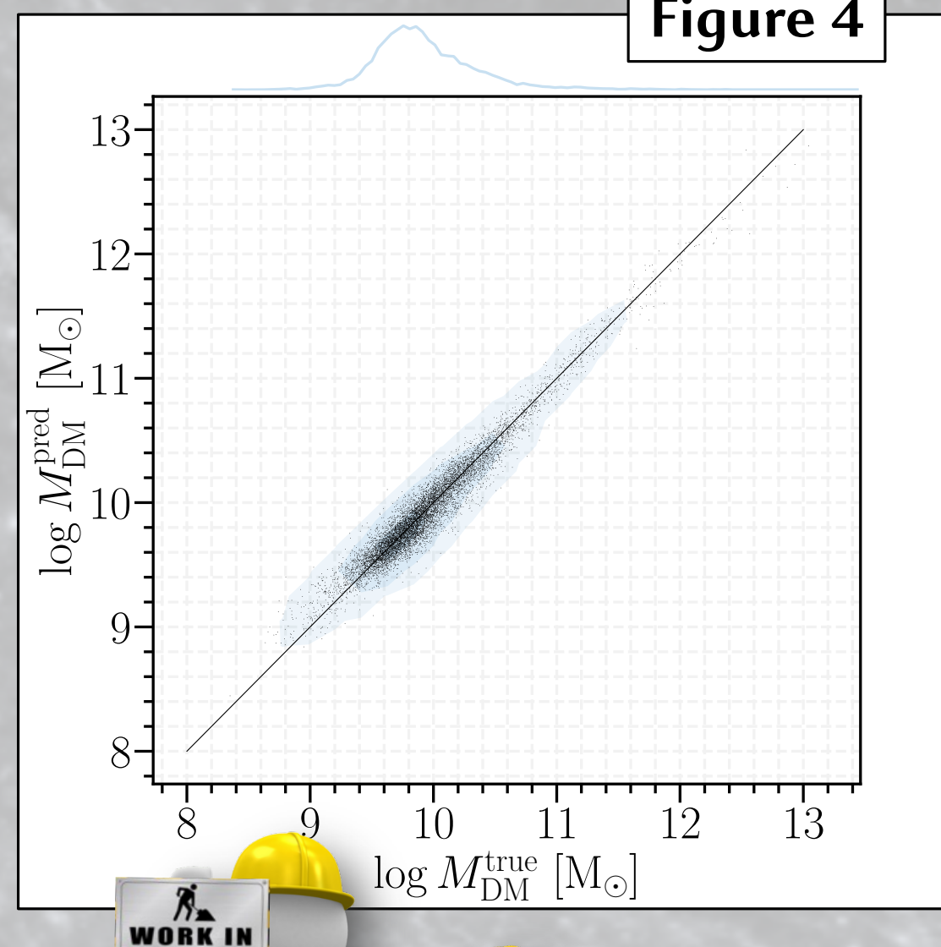
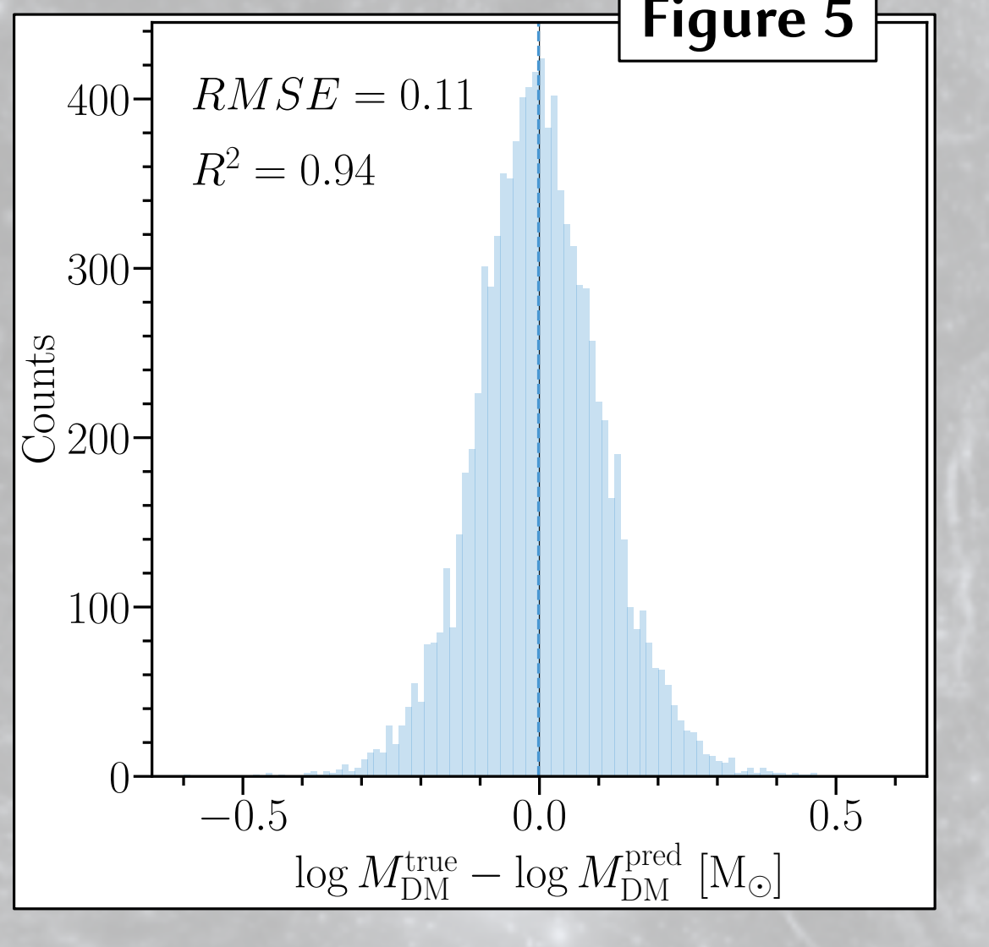
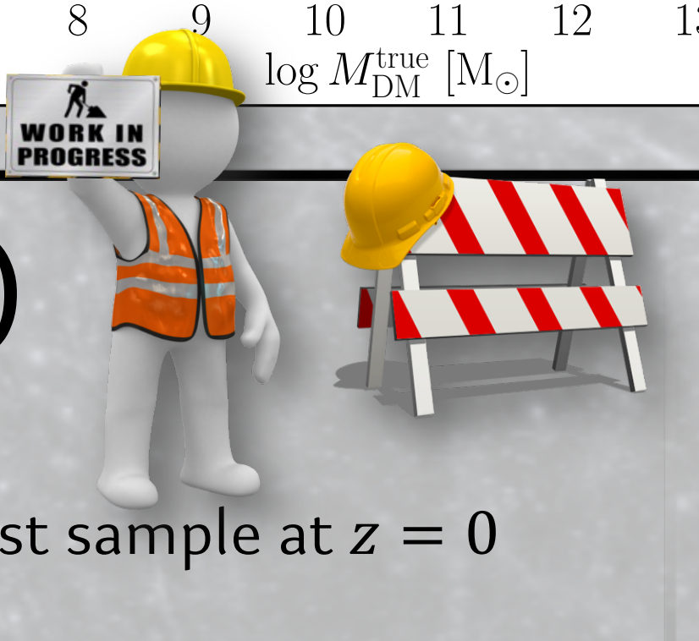


Figure 5



Conclusions & future perspectives (<u>Cannarozzo et al., in preparation</u>)



- High strength of inference of DM mass by gas, stellar, and BH masses
- High accuracy in predicting DM mass, with a scatter of around 0.11 dex between the actual values of DM mass and the predicted values of the test sample at $z = 0$
- This scatter significantly decreases towards high masses (about 0.04 dex in systems with $\log(M_{DM}/M_\odot) \simeq 12$)
- The analysis at $z = 0.5, 1, 2$, and 3 of TNG100-1 reveals the capability of EBM in tracing the back-in-time evolution of the strength of inference for the used properties

○ <u>*Future:*</u> extending the analysis to TNG50-1 and TNG300-1 to understand whether and to what extend the inference depends on different volumes and resolutions

○ <u>*Future:*</u> finding a functional form able to better constrain the DM mass estimates in real galaxies exploiting several observables $f(M_{\rm DM}|\mathcal{D})$

Contact me!

For any question, curiosity, or anything else, please, do not hesitate to reach me at

✉

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Curiosity! The background consists of a mix between <u>a computer-generated image of a human profile</u> and <u>the composite image of the full TNG100-1 box which overlays a projection of the dark matter density field and shocks</u>.