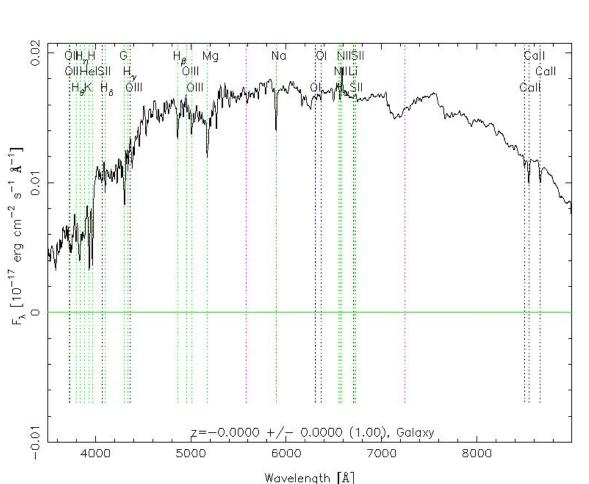


By: Aniket Naik, Anthony Vetturini, Arnav Garcha, and Changcheng Ji

### **Background and Introduction**

The Sloan Digital Sky Survey (SDSS) has spent decades collecting data in an effort to make a map of the universe, and it has documented more than 2.86 million galaxies and 960,000 quasars<sup>1</sup>. One portion of its data collection includes atomic emission line observations, as these readings can inform us of astrophysical phenomena, such as the rate of star formation within galaxies<sup>2</sup>. Herein, we use this atomic emission line data to create a predictive model that looks to predict the mass of an observed galaxy from the SDSS data.



An example of an emission line reading. The "smooth" black line is the continuum of the measurements. The narrow troughs (or spikes) are specific emission lines cause by electron transitions. Here, the vertical lines name the emission line at a measured wavelength from the SDSS.

https://classic.sdss.org/dr5/algorithms/spectem plates/spDR2-022.gif

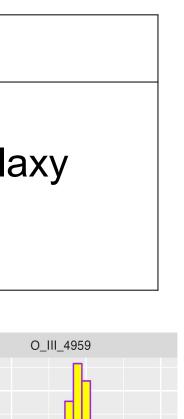
### **Exploratory Data Analysis**

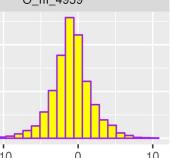
The SDSS dataset contains the strengths of <u>10 emission lines</u> measured across <u>21,046</u> galaxies. We have emission data for various Hydrogen, Oxygen, and Nitrogen ionization states of varying wavelengths and are looking to predict the mass of the galaxy

<b>Predictor Variables</b>	<b>Response Variable</b>		
$ \begin{array}{c c} H_{Alpha} & O_{III\_4959} & N_{II\_6584} & S_{II\_6717} \\ H_{Beta} & O_{III\_5007} & N_{II\_6548} & S_{II\_6731} \\ H_{Gamma} & O_{II\_3729} \end{array} $	Estimated Mass of Gala (log <sub>10</sub> solar mass)		
Data Transformation	O_III_4959 90002000 -		
Why? Predictor variables were heavily skewed leading to high error in prediction	1000 - 50 100 150 20010		
1. Negative emission line values were removed. This removed	Example Initial Predictor  Transform Distributions		
9,455 data points	N_II_6584 O_II_3729 N_II_6584 12 - 11 - 11 - 11 - 11 - 11 - 11 - 11 -		
2. The remaining data was first squared then log-transformed	Se 10 - Se 10		
3. The squared values were then log <sub>10</sub> transformed	Figure 1. The transformed predictor variates show similar distributions when measured		

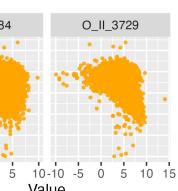
show similar distributions when measured against the response. The original data (left) has different distributions when measured against the response.

# **Predicting Galaxy Mass from SDSS Emission Data**





ned Predictor ributions



ables (right)

• In the non-transformed training, best-subset selection with linear regression eliminated 3 predictor variables: H<sub>gamma</sub>, O<sub>III 4959</sub>, and N<sub>II 6548</sub>. In the transformed training, all of the predictors were retained (hence the same MSE as standard linear regression). • With the transformed data, XGboost produced the smallest MSE (Fig 2, Fig 3). In the non-transformed data, MSE was minimized with XGBoost.

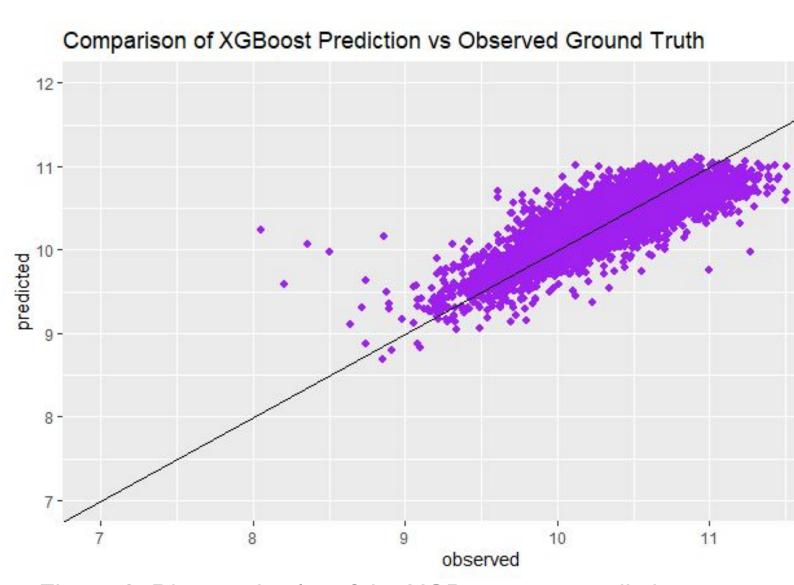


Figure 2. Diagnostic plot of the XGBoost test prediction on transformed data compared to ground truth.

### Conclusions

- Transforming the data as described in the Exploratory Data Analysis led to smaller MSEs despite removing 9,455 data points resulting in a more accurate predictive model.
- We have successfully modelled the relationship between galaxy emission line data and the predicted log solar mass of a galaxy
- We have found that the best predictive model is found using XGBoost with the transformed data with an MSE of 0.02576

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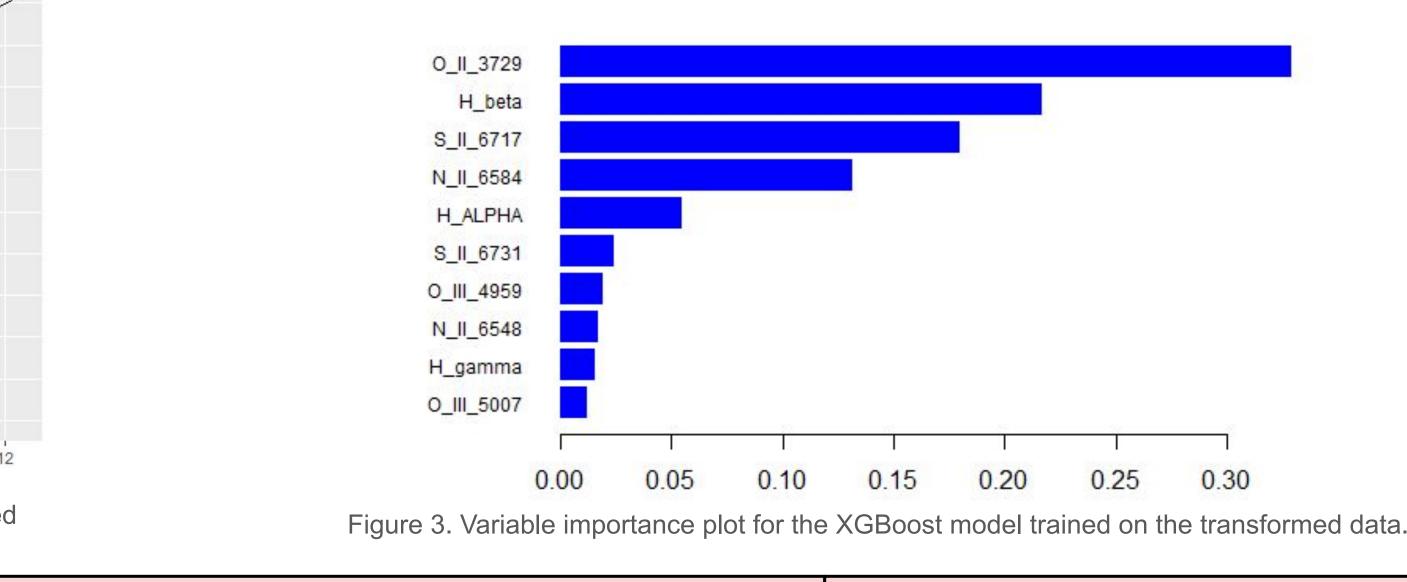
### Methods

• The same training and test set were used for each model. A 70/30 training and test split were used. A random seed was imposed. • We used several statistical learning models, including linear regression, random forest, regression trees, and XGBoost to predict galaxy mass. • To evaluate the models, mean squared error (MSE) of the ground truth mass and the predicted mass from test set were calculated.

### **Analysis and Results**

Table 1. Results for the test set MSEs for the non transformed predictor variables (right) vs. the transformed dataset (left) The transformed dataset performed marginally better with XGboost and Regression Trees.

Non Transformed Data		Transformed Data	
MSE	Model Type	MSE	
0.12305	Linear Regression	0.08549	
0.12304	LR-BSS	0.08549	
0.10577	Regression Tree	0.10233	
0.07637	Random Forest	0.06718	
0.05114	XGBoost	0.02576	
	MSE 0.12305 0.12304 0.10577 0.07637	MSEModel Type0.12305Linear Regression0.12304LR-BSS0.10577Regression Tree0.07637Random Forest	



1) Funding for the Sloan Digital Sky Survey V has been provided by the Alfred P. Sloan Foundation, the Heising-Simons Foundation, the National Science Foundation, and the Participating Institutions. SDSS acknowledges support and resources from the Center for High-Performance Computing at the University of Utah. The SDSS web site is www.sdss.org. 2) von Der Linden, Anja, et al. "Star formation and AGN activity in SDSS cluster galaxies." Monthly Notices of the Royal Astronomical Society 404.3 (2010): 1231-1246.



0.30

### References