AGNet: Weighing Black Holes Using Machine Learning

ILLINOIS
NCSA | National Center for Supercomputing Applications

Joshua Yao-Yu Lin*, Sneh Pandya*
Devanshi Pratap, Xin Liu, Matias Carrasco Kind

Introduction

Goal

To develop a neural network that can predict active galactic nuclei (AGN) redshift and SMBH mass using quasar light time series.

Supermassive black holes (SMBH) are ubiquitously found at the centers of most galaxies. Measuring SMBH mass is important for understanding their origin and evolution. We train Machine Learning (ML) algorithms that learn from the Sloan Digital Sky Survey (SDSS) Stripe 82, DR7, and Stripe 82 Damped-Random-Walk (DRW) data for a sample of $\sim$10,000 quasars to map out the nonlinear encoding between black hole mass and multi-color optical light curves (Sun, 2020).

Motivation

We present an algorithm that weighs SMBHs using quasar light time series, circumventing the need for expensive spectra. We train, validate, and test neural networks that directly learn from the Sloan Digital Sky Survey (SDSS) Stripe 82 data. We find a 1σ scatter of 0.35 dex between the predicted mass and the fiducial virial mass based on SDSS single-epoch spectra. Our results have direct implications for efficient applications with future observations from the Vera Rubin Observatory.

Data and Methodology

Data Matching

We adopt multi-color photometric light curves from SDSS Stripe 82 as our spectral data. Our baseline sample consists of $\sim$10,000 quasars in the Stripe 82 survey. We assume the virial black hole mass estimates from the SDSS DR7 catalog as the ground truth, and match the two according to their equatorial coordinates. We additionally adopt M_i and redshift (z) as features in predicting SMBH, and further adopt time series features, τ and σ, from Damped Random Walk fitting parameters.

Data Preprocessing

We find that in order to extract relevant features from our light curves and matched data, we benefit from preprocessing our data. We compute the colors $(u-g, g-r, r-i, i-z)$ colors by taking the mean *ugriz* magnitudes across an observational epoch from our light curves. We match this with our DR7, Stripe 82, and DRW datasets. To standardize the effects of our features, we use the scikit-learn *StandardScaler* to remove the mean and normalize the variance.

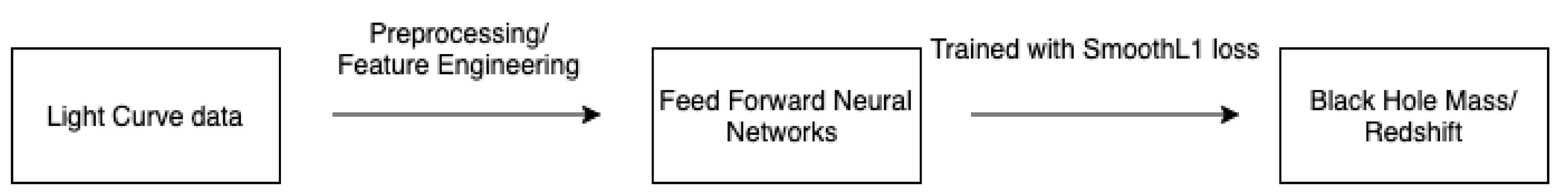

Figure 1: *AGNet Pipeline.*

Neural Networks

Network Architecture

We use feedforward neural networks (FNN) to predict AGN redshift and SMBH mass. We use 5×64 neuron hidden layers and a one neuron output layer. Dimension of input layer is 10 neurons for redshift prediction, and 9 neurons for mass prediction.

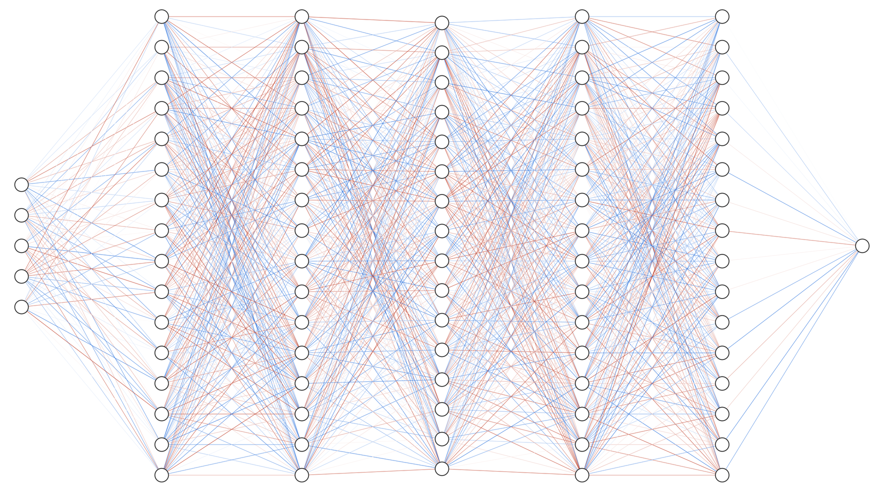

Figure 2: *AGNet Architecture.*

Network Implementation

AGNet is designed to predict AGN redshift and SMBH mass from quasar light time series. In the redshift prediction implementation, we train feedforward neural networks (FNN) to predict redshift using $ugriz$ magnitudes and associated colors. We compare these to the spectroscopic redshift ground truth from SDSS. We further use FNNs to predict SMBH mass using $ugriz$ colors, M_i, redshift, and additional light curve features τ and σ. If spectroscopic redshift (spec-z) is available, AGNet provides a fast and automatic way to predict SMBH mass. In scenarios where spec-z is absent, AGNet has the ability to predict redshift and use the predicted redshift as a feature in predicting SMBH mass. We train our FNN's with the SmoothL1 loss function and for 50 epochs. We use AdamW optimizer with the default learning rate set to 0.01.

Find our paper at: https://arxiv.org/abs/2011.15095 (QR code above)

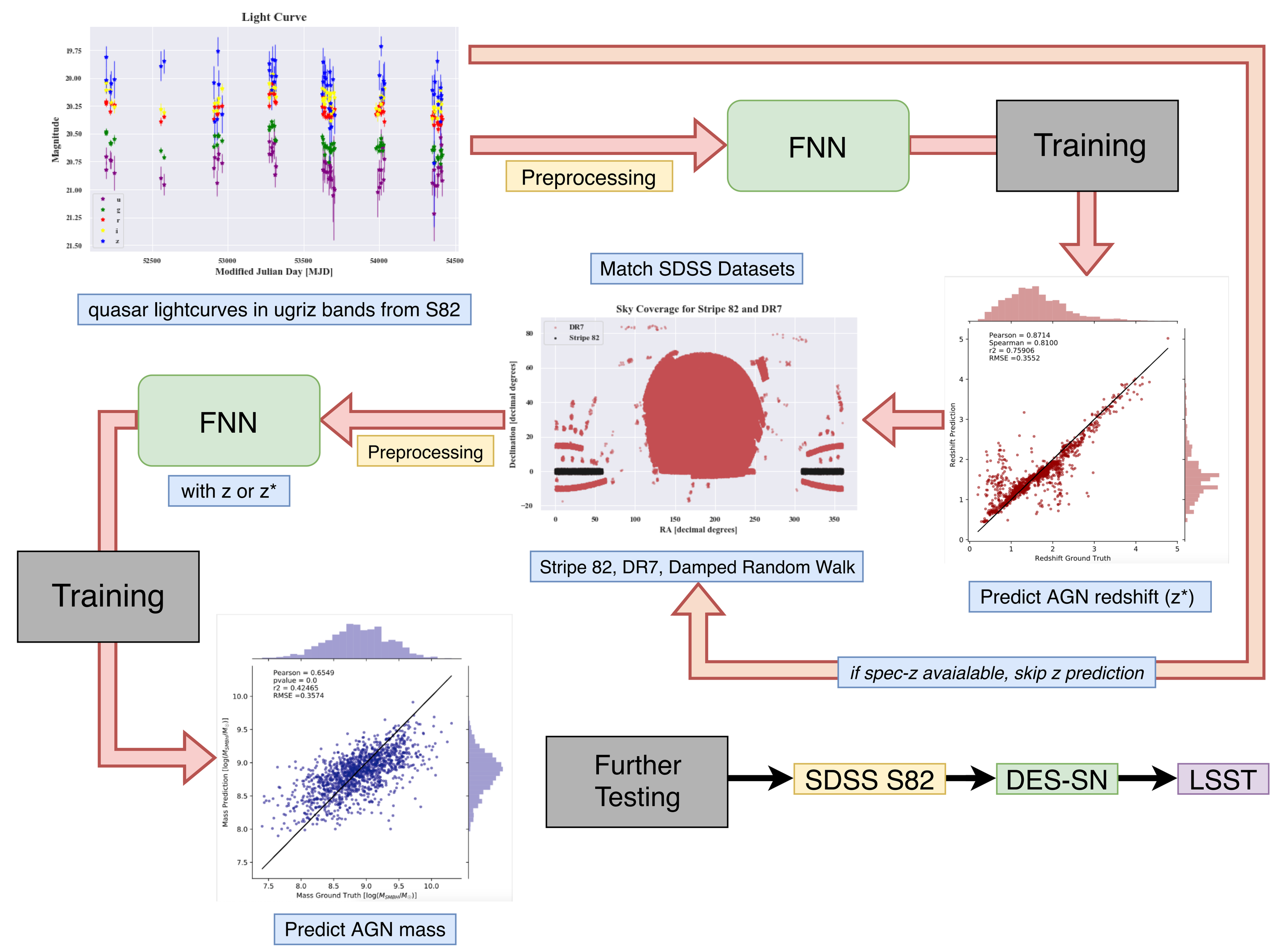

Figure 3: *AGNet Implementation Flowchart*

Testing and Results

We split our data into an 85/15 training and testing set. We evaluate performance on a testing set of $\sim$2000 quasars. Our mass performance yields an uncertainty already comparable to the systemic uncertainty of our "ground truth" virial black hole mass estimates. Variation in redshift prediction for low z $(z < 2)$ is well understood and caused by quasar color degeneracy.

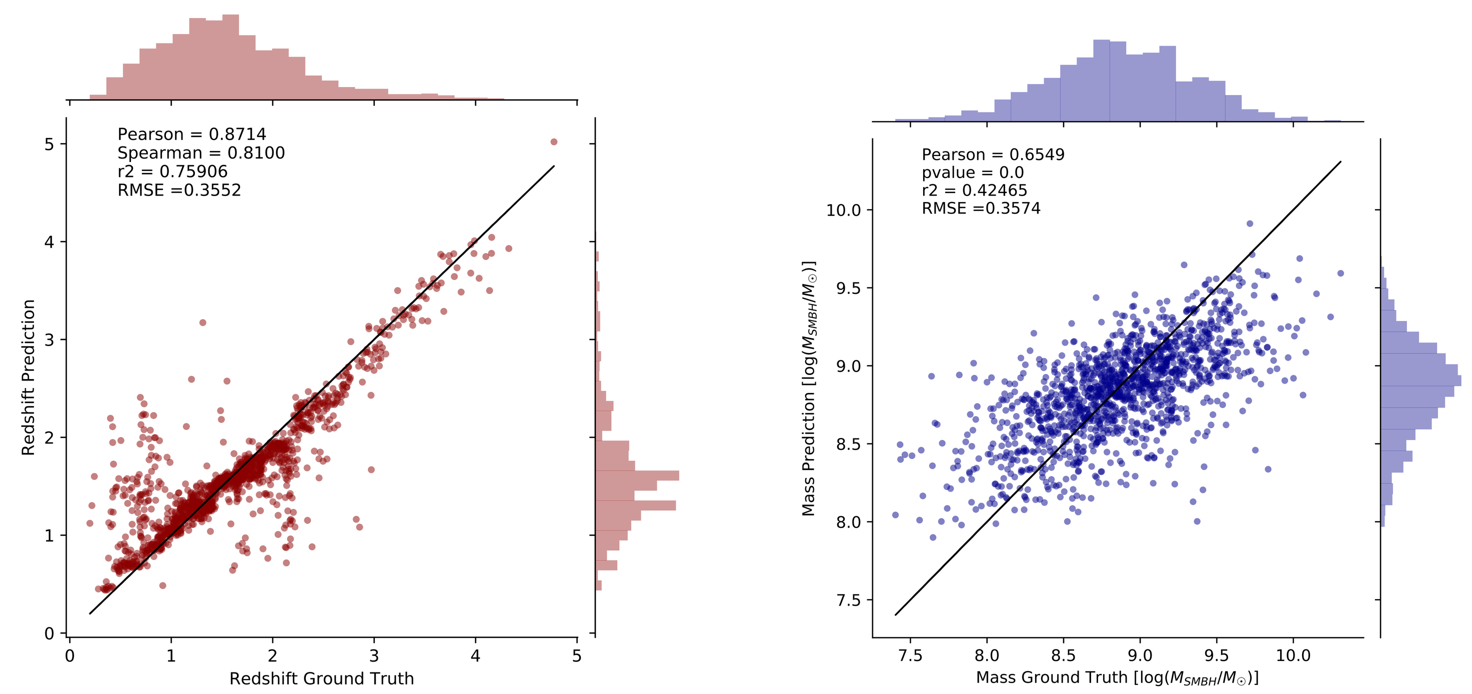

Figure 4: *AGNet redshift and mass results*

Comparison to KNN

Summary Statistics

ML algorithm	Features	Parameters	RMSE	R^2
AGNet	colors and bands	redshift (z)	0.355	0.759
KNN	colors and bands	redshift (z)	0.386	0.715
AGNet (w spec-z)	colors, τ, σ, M_i, z	SMBH mass	0.357	0.425
KNN (w spec-z)	colors, τ, σ, M_i, z	SMBH mass	0.370	0.369
AGNet (w/o spec-z)	colors, τ, σ, M_i, z*	SMBH mass	0.401	0.272
KNN (w/o spec-z)	colors, τ, σ, M_i, z*	SMBH mass	0.398	0.283

Table 1: Summary Statistics

Figure 5: *Summary Statistics*

Discussion and Next Steps

We have shown that AGN SMBH mass and redshift can be efficiently estimated using just quasar light time series. The success in redshift predictions was initially shown in Pasquet-Itam & Pasquet, 2018, however this is a pioneer effort in applying a DL architecture to retrieve quasar masses. In the past, we have explored transfer learning techniques and CNN architectures. In the future, exploring other modified network architectures and sampling data from other surveys would be advisable.

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