Robust Estimation of the Optical Depth Using 21 cm Data and Machine Learning

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Background

- The Epoch of Reionization (EoR) refers to the era in which the first luminous objects in the universe were formed (6 <z < 20).
- Hydrogen Epoch of Reionization Array (HERA) is a radio telescope dedicated to observing large scale structure during and prior to the EoR, particularly probing from the 21cm line.
- One goal of the HERA team is to predict the "optical depth", a unitless value to describe the total reionization process. Finding the *optical depth* is important for the calculation of the mass of the neutrino.
- We can design convolutional neural networks (CNN) that input observational data of the 21cm field produced by HERA and output the predicted *optical depth* by training the CNN on snapshots from *simulations* of reionization.
- We use two simulations of reionization for this purpose: 21cmFAST and Zreion.
- We can create a diverse set of training data by standardizing the reionization histories between two semi-analytical models, which in principle will increase the efficacy of the neural networks.

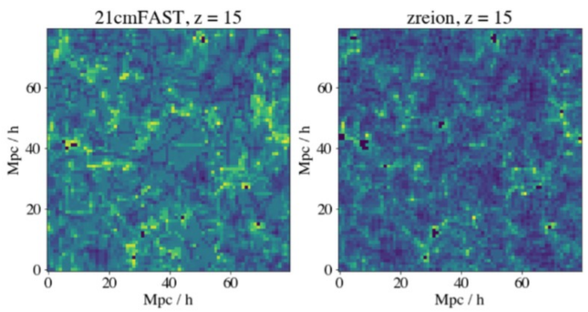

Figure 1: Two simulations from 21cmfast and zreion with the same underlying density field realization and ionization history, showing the different morphologies of brightness temperature emission.

Abstract

We examine methods to robustly determine the optical depth to reionization from future 21 cm datasets in a manner that is robust against detailed assumptions about the reionization process as encapsulated in simulations. In particular, we construct a training set of simulations using two different semi-numerical models, which use the same underlying density field realization and are matched so that they produce identical optical depth and ionization histories but differ in the detailed morphology of the 21 cm emission, and in their power spectra. We focus the machine learning algorithm on extracting the volume ionization fraction of hydrogen from the simulations as the most robust observable quantity and the one for which 21 cm measurements will provide uniquely. We demonstrate a neural network architecture which can robustly measure the ionization history in the presence of random noise and spatial filters like those which will affect the next generation of reionization measurements.

Methods

- Built a simulator translator that translates free parameters of one simulation to the free parameters of the other such that those parameters would produce equivalent ionization histories.
- To do this, I programmed a Neural Network written in pytorch to predict a ionization history from its free parameters alone. I then trained the model on a 1000 21cmFAST and Zreion simulations.

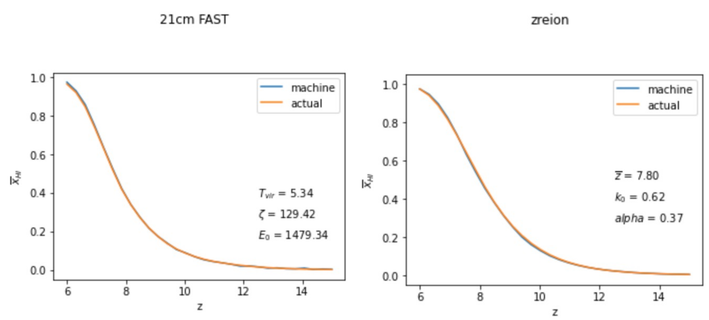

Figure 2: Sample of the Emulator's performance predicting the ionization history curve on test data for 21cmFAST and Zreion.

- To optimally design this neural network, I had to program a custom loss function that penalized heavily when the network predicted curves that did not line up with physical reality: the curves must be smooth and between 0 and 1.
- Likewise, I modified the network architecture such that it preformed optimally on the test data (number of layers and number of nodes on each layer).
- From here, I implemented a chi-squared minimization package (lmfit) to best match a predicted simulation's ionization history with the other simulation's predicted ionization history. This effectively serves as a fast simulator translator.

Results

- Functional translator can map one simulations parameter space to the other

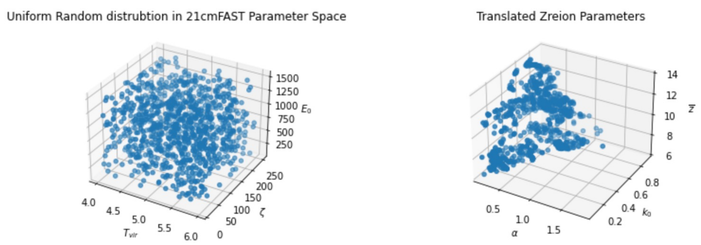

Figure 3: Mapping of a uniform random distribution of 21cmFAST params to Zreion params.

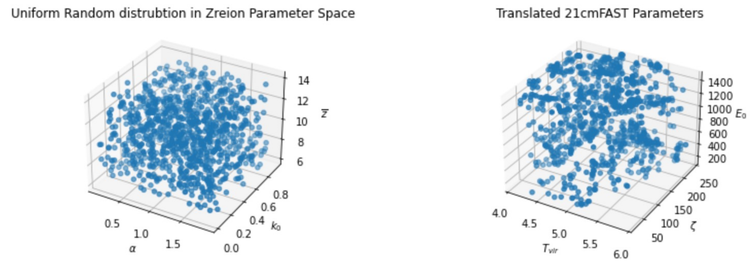

Figure 4: Mapping of a uniform random distribution of Zreion params to 21cmFAST params.

- We show that our network can recover ionization history accurately regardless of the simulation type.
- Output parameter space from the translator fits with in parameter bounds for both simulations.
- We see clumping after both translations, which tells us details about the specific nature of the translation.

Discussion

- We can use my translation program to predict the optical depth for a given set of 21cmFAST or Zreion Parameters

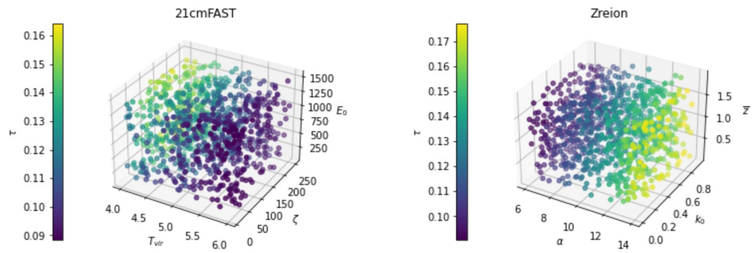

Figure 5: Predicted optical depth (tau) for a given set of 21cmFAST and Zreion free parameters

- We can use these optical depth predictions from my translation program towards creating a more diverse training data set for the CNNs using HERA data to measure the optical depth.
- From this we find that of the factors affecting optical depth, the 21 cm measurement is relatively insensitive to the cosmology and, in "inside-out" models of ionization, to density field as well.
- With more fine tuning of this program and toy models, we hope to later this year train the CNNs to accurately measure the optical depth to reionization.
- Astrophysicists can then use the measured value for optical depth combined with the constraints from measurements from the Simon's Observatory to calculate the mass of the Neutrino.