Foreground separation of interferometric 21cm cosmological observations using convolutional neural networks

Lisa Dayaram[1,2][0000−0001−9711−0107], Devin Crichton[1,3], and Anban Pillay[1,2][0000−0001−7160−6972]

[1] University of KwaZulu-Natal, Westville Campus,Durban,4000, South Africa
[2] School of Mathematics, Statistics and Computer Science
[3] Astrophysics and Cosmology Research Unit
ldayaram@gmail.com

Abstract. The Hydrogen Intensity and Real-time Analysis eXperiment (HIRAX) is an array of radio telescopes being deployed at the Square Kilometre Array in South Africa, which will generate terabytes of interferometric data daily. This paper investigates the use of convolutional autoencoders to separate cosmological signal from the foreground contaminations in the context of 21cm observations.

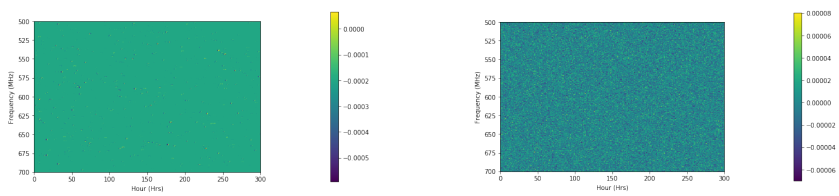
HIRAX is a radio telescope array or radio interferometer that aims to calculate the statistical distribution of matter through the different epochs of time in an attempt to measure the expansion history of the universe. A radio interferometer is an array of radio telescopes, used to study the naturally occurring radio light from stars, galaxies, black holes and other astronomical objects. These telescopes collect weak radio waves, bring it to focus, amplify it and make it available for analysis. The images created contain foreground contaminants. The foreground of an image refers to a bright astrophysical radio source that contaminates the target signal. Our goal is to separate these contaminants from the image in order to accurately trace the 21cm signal.

Foreground separation is a significant task in radio astronomy [2][13]. It is important to reduce the risk of these contaminants in the data to avoid the foreground uncertainties biasing the analysis. In recent years, deep learning algorithms have become increasingly popular among astronomers. Modern telescopes are capable of producing data faster than astronomers can process. The rapid growth in data size and complexity demands data-driven science in astronomical analysis. The efficacy of deep learning techniques [3][11] in related domains prompted the use of Convolutional Neural Networks [5] in classifying the foreground contaminants and the target signal.

This project aims to create a filter to separate the cosmological signal of interest, more specifically the 21cm emission line, from the foreground contaminations using deep learning techniques.

A key point concerning the identification of the foreground is its spectrally smooth nature as a frequency function which, in principle, allows it to be separated from the target 21cm signal. The network used in this work is an autoencoder with an underlying convolutional neural network (CNN) architecture. The convolutional layers serve to convolve the input images, effectively preserving spatial dependence whilst the hidden layers of the autoencoder act as an effective feature detector, in this case identifying the signal data from the foreground contaminants. The network was evaluated using the loss and accuracy of predictions.

The visibility timestreams (input data) of HIRAX observations were simulated using Draco (a pipeline for the analysis and simulation of drift scan radio data), along with the following python packages: Driftscan, Cora, Caput. Simulated or synthetic data plays an integral role in the interpretation of observations. Due to the varying properties and calibrations a telescope may have it becomes challenging to keep track of all the anomalies that arise, which adds further constraints on the task of identifying and separating the target signal from the foreground.



(a) Prediction (b) Signal test data

Fig. 1: Graphical results of a single channel, over frequencies ranging from 500 -700MHz over three days (72 hours), show a significant subtraction of contaminants. The predicted outcome (a) is compared against the signal test data (b).

Foregrounds are several orders of magnitude more intense than the 21cm signal and are highly correlated hence we track the progress of the model by plotting the predicted outcomes, the signal-only data and the original (contaminated) inputs - resulting in graphs of frequency (MHz) against time(hrs). The colour-bars generated aids in calculating the difference in magnitudes of what is observed from the output vs. the signal-only data and is an estimate of how well the model performed. From the results obtained during this experiment, the network is able to recover some of the signal and has managed to subtract a significant amount of the foreground contaminants.
We conclude that deep learning techniques have the potential to perform well in this domain.

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