Retrieval of atmospheric temperature and humidity profiles form radio occultation observations using machine learning

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Image on cover page: A sample result from of the retrieval

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1 Introduction

Earth's weather is highly nonlinear in nature. For various applications, it needs to be monitored continously for the changes in the tempearture and water vapor concentations. Radiosonde observations are the most reliable measurements of this purpose. However, these observations are very sparse and not available over the oceans. Moreover, they have manual dependency too. Sounders onboard satellites remove this dependency and also provide observations globally at high spatial and temporal resolutions. Infrared (IR) sounders can provide water vapor structure in clear-sky conditions but they have their own limitations during cloudy and precipitating environment. Microwave (MW) sounders are also sensitive to heavy precipitation which limits there use in extreme weather events. The radio occultataion (RO) measurements from global navigation satellite system (GNSS) have the advantage of monitoring Earth's atmosphere in all weather conditions, with high vertical resolution. The RO measurements does not require calibration which makes them more reliable. With the launch of various constellations like Constellation Observing System for Meteorology, Ionosphere, and Climate (COSMIC), RO observations are now available globally at high spatial resolution too.

An RO occurs when a receiver in low-Earth orbit (LEO) views a GNSS satellite (e.g., the US Global Positioning System, GPS) as it sets or rises behind the Earth's atmosphere. The measured signal phase and amplitude are analyzed to derive atmospheric refractivity. The atmospheric state variables (p, q and T) can be derived from the inversion of atmospheric refractivity observations. Operationally, this inversion is done using optimal estimation which is based on Bayesian theory. It requires the *a priori* knowledge of the atmospheric state variables (p, q and T) which are obtained form some model output. The use of *a priori* can be avoided by developing empirical relationship among the atmospheric state variables and the RO observations using a collection of large dataset. This will reduce the time of retrieval too.

Machine learning (ML) consists of algorithms that learn and establish relationships, also termed as training, among the dependent and independent variables from a collection of dataset. Training an ML algorithm is one time process but is computationally expensive. As high speed computers are nowadays easily available, application of ML algorithms have become ubiquitous. Deep learning is a subfield of ML that is based on neural networks, which are highly flexible differentiable functions that can be fit to data. Neural networks consist of a hierarchy of layers that contain nodes performing weighted (non)linear transformations of their inputs, through a series of hidden layers, to the desired output.

In this study, we have developed a deep learning based algorithm for the retrieval of thermodynamic profiles using RO observations. The structure of the ducument is as follows. The deep learning ML algorithm used in this study is discussed in the following section. The data used and the procedure for preparing the training dataset is described in section **??**. The "Results and discussion" section is devoted to the analysis of the performance skill of the developed algorithm.

2 Deep neural network

Neural networks, also known as artificial neural networks (ANNs), are a subset of machine learning and are at the heart of deep learning algorithms. Their name and structure are inspired by the functioning and structure of biological brain. ANNs are comprised of a node layers, containing an input layer, one or more hidden layers, and an output layer. Each node, or artificial neuron, connects to another and has an associated weight and threshold. If the output of any individual node is above the specified threshold value, that node is activated, sending data to the next layer of the network. Otherwise, no data is passed along to the next layer of the network. A deep neural network (DNN) is an ANN with multiple hidden layers between the input and output layers (ref).

3 Data and methods

We have developed the DNN model using the simulated refractivity observations. The temperature, pressure and water vapor profiles over the Indian region (Lat:, Lon:) are extracted form the three hourly European Centre for Medium Range Weather Forecasting (ECMWF) analysis for the year 2020 and 2021. The refractivity forward model (ref) is used to simulated the refractivity observations using the ECMWF extracted profiles. The atmospheric profiles used here have 36 pressure levels evenly distributed from 1000 to 1 hPa.

The training dataset of DNN is created by setting the simulated refractivity observations, lat, lon, height and time as input (independent) variables while the temperature, pressure and water vapor as output (dependent) variables. Then n-layer network structure is built (one input layer, n-2 hidden layer and one output layer) and DNN is trained. Rectified linear unit (ReLU) is used as the activation function.

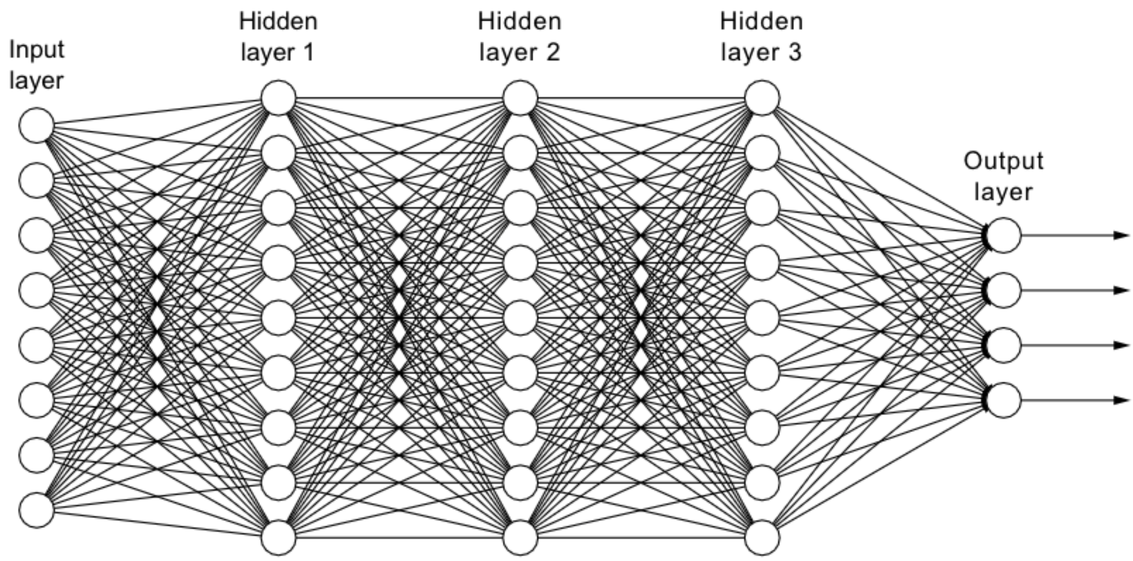

Fig. 1: Deep neural network architechture

4 Results and discussion

5 Conclusion