An assessment of Machine Learning methods for emulating 2-D quasi-geostrophic dynamics

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Introduction

❖ This work will act as a survey of Machine Learning methods applied for prediction of geophysical fluid dynamics of the atmosphere or ocean. The Machine Learning methods will be applied in an idealized context to evaluate and compare the performance of atmospheric dynamics.

❖ For the quasi-geostrophic system, we use the simple implementation by Demeayer et al [1] in which the mid-latitude atmospheric variability is represented using the atmospheric stream functions, temperature fields and land temperature fields.

❖We extract the geopotential height field as a 2D 'image' to construct a temporally consistent set of 2D snapshots for experimentation. Via this construction we generate an 'image time series'.

❖The geopotential heights give the altitude of a point or layer in the atmosphere. It is represented in terms of the potential energy between a point and sea level which is dependent on the exact gravity value at that point.

❖We have the geopotential height being defined as below in equation (1).

$$Z_g(h) = \frac{\Phi(h)}{g_0} = \frac{1}{g_0}\int_0^h g(\phi, z)\, dz \qquad (1)$$

Methods

The methods used in this regression-based problem are as follows. The hyperparameters which are trained by Optuna are learning rate, optimizer, drop out, number of layers in the network and the number units in each layer.

❖ Feed Forward Neural Network (FFNN) - The FFNN consists of neurons or processing elements which are connected to each other via weights. An output is produced by passing the weighted sum of the input signals through an activation function.

❖ Convolutional Neural Network (CNN) - The CNN have layers which include the convolutional layer, non-linearity layer or activation function and pooling layer.

❖ Convolutional Neural Network with fully connected output layer (CNNFCNN).

Other methods used in this regression-based problem are:

❖ U-Net- This is a fully convolutional neural network with a combination of first decreasing or contracting path (encoder - left side) and then increasing or expansive resolution layers(decoder - right side) in which the context and localization are captured, respectively. The U-Net we follow is from [2].

❖ Recurrent Neural Network (RNN) - (RNNs) provide a mechanism to account for the temporal context of the training data. Here, we use a simplified form of RNN called reservoir computing (RC), which permits rapid training at low cost, and has produced successful results in many applications focused on predicting dynamical systems.

❖ Convolutional-Long Short-Term Memory Network (Conv-LSTM) - Conv-LSTMs combine the spatial dimension reduction of CNNs while accounting for the temporal dynamics of the system as the LSTM.

Results

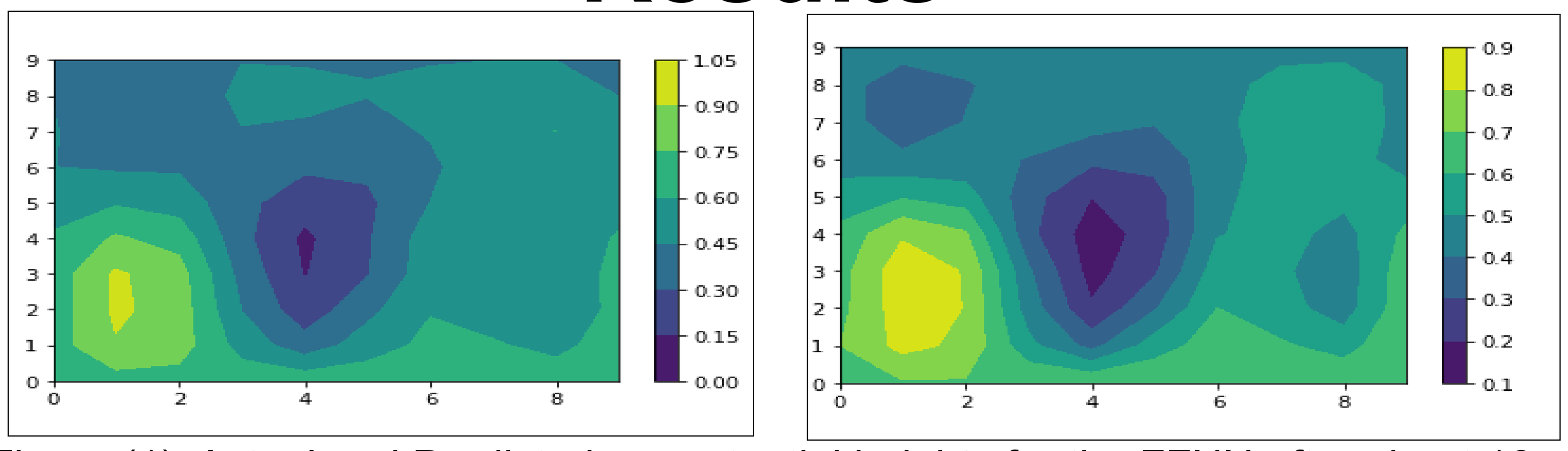

Figure (1): Actual and Predicted geopotential heights for the FFNN after about 16 minutes (16.15 minutes)

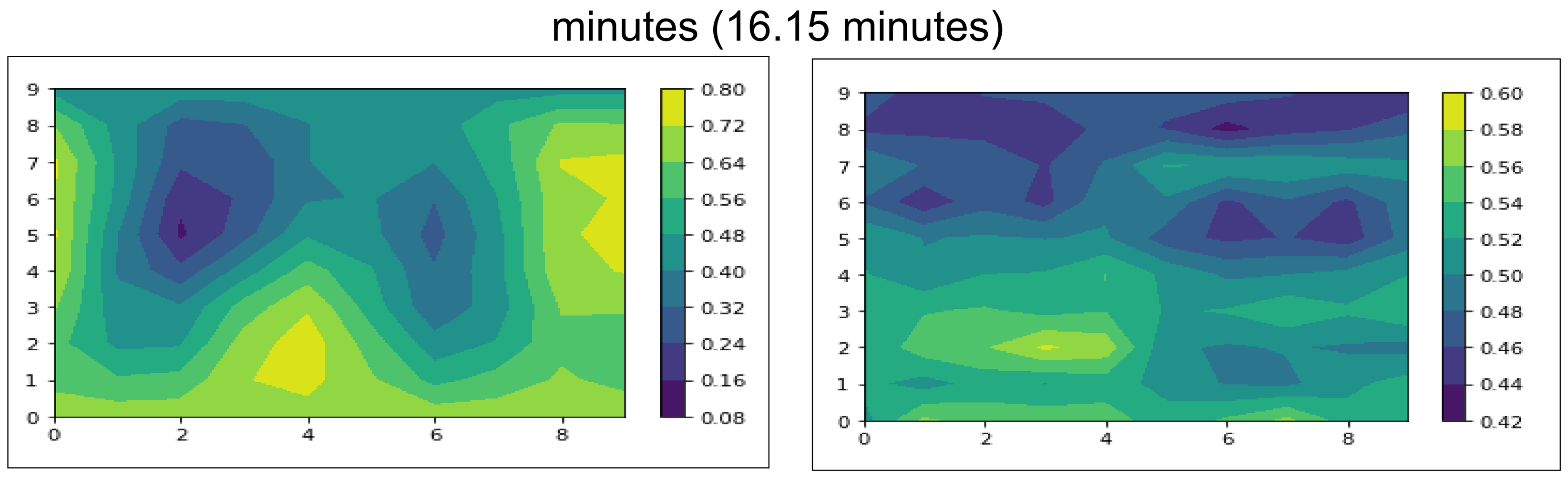

Figure (2): Actual and Predicted geopotential heights for the CNN after about 16 minutes

Results Cont'd

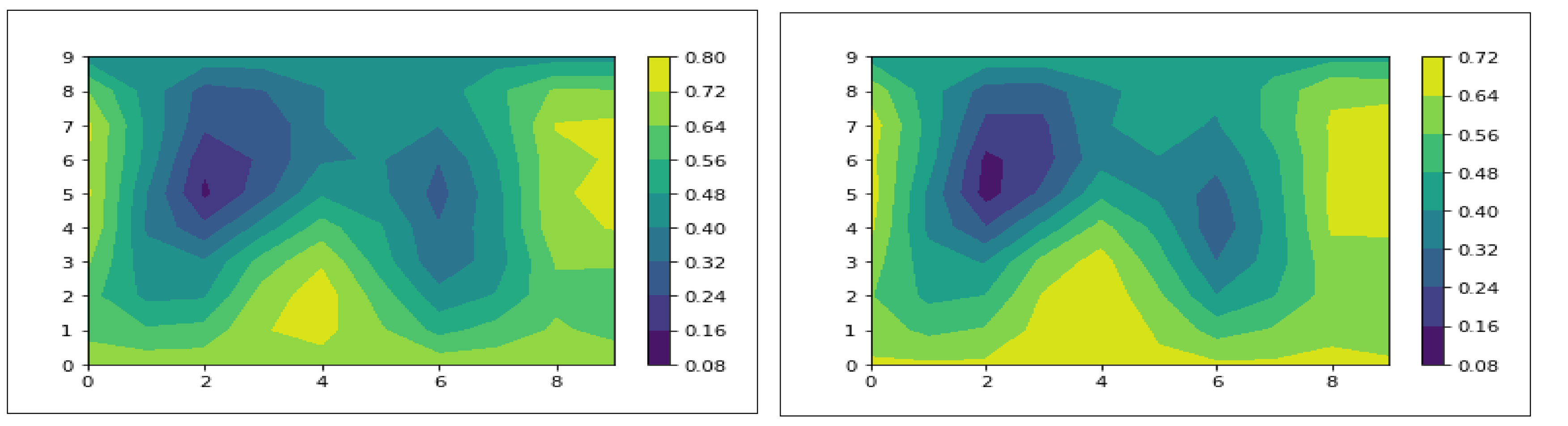

Figure (3): Actual and Predicted geopotential heights for the CNNFFNN after about 16 minutes

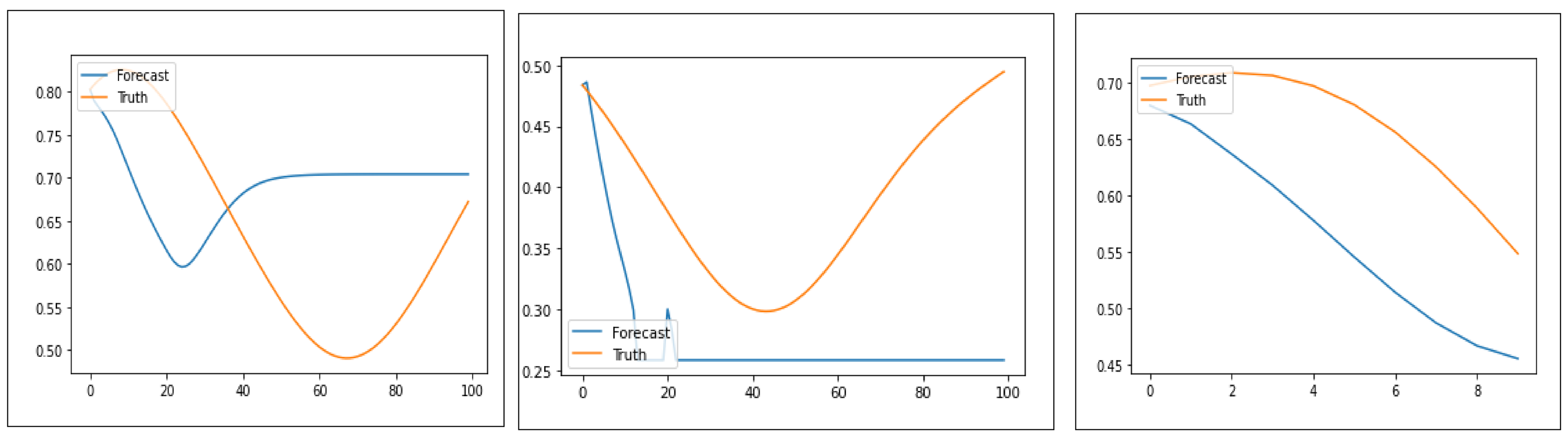

Figure (4): Forecast Series for the 3rd dimension for the CNNFCNN (number of layers optimized), U-Net and the Conv-LSTM respectively

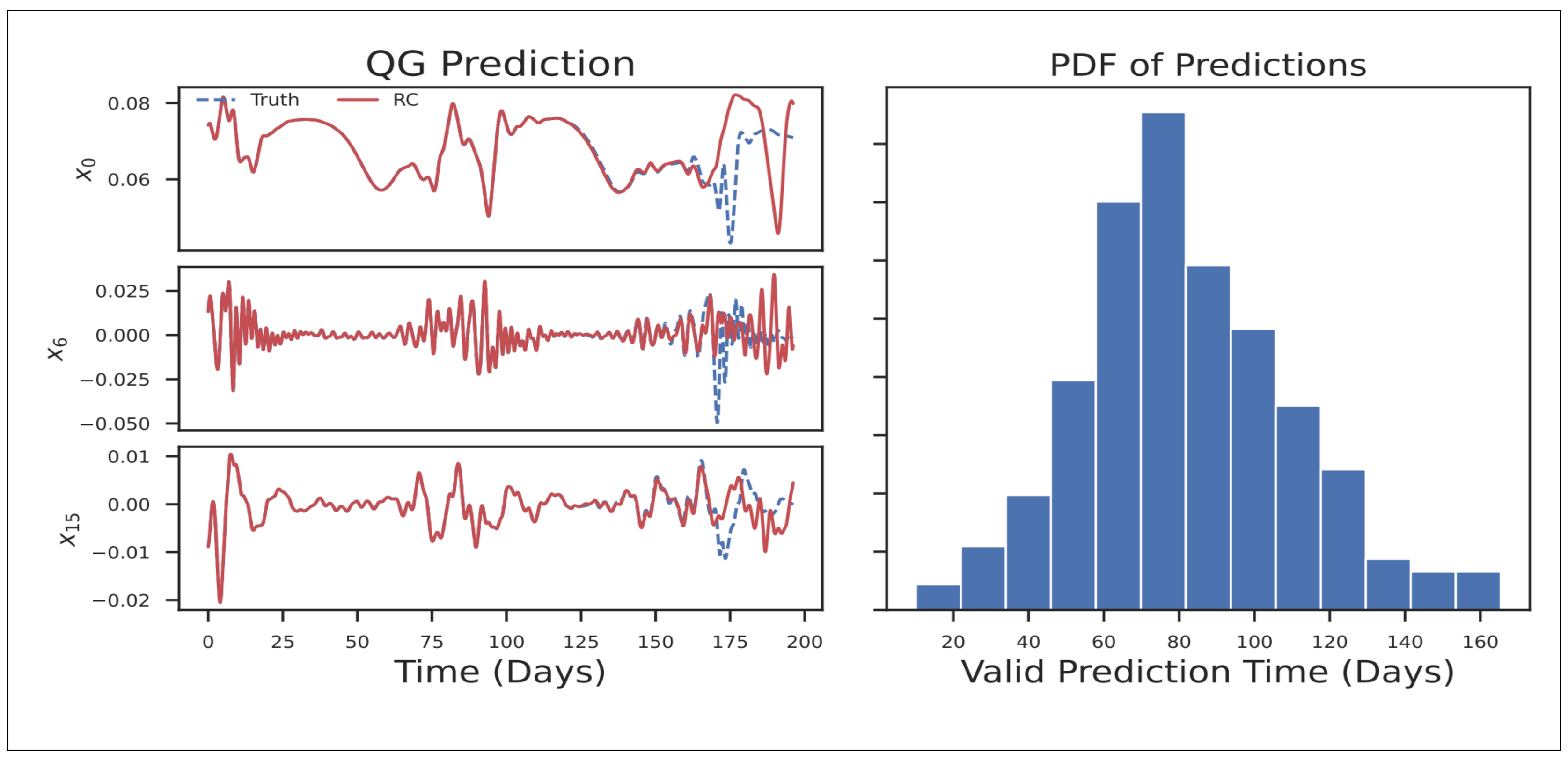

Figure (5): Actual and Predicted Feature for the 1st, 7th and 16th modes using RC

Discussion/Conclusions

❖ From Figures (1) and (2), the FFNN is performing better than the CNN. Thus, it can be stated, from Figure (3), that the fully connected layer (FC) has the most 'predictive power' or is doing most of the work in the CNNFFNN.

❖From Figure (4), it is seen that, even though the snapshot of the images corresponds well with each other, the series of the forecasts for the random 3rd dimension does not follow the truth. This thus implies that a more rigorous investigation is required (other than the snapshots) when comparing the actual and the predicted feature of the image time series.

❖From Figure (4), the most promising model, the Conv-LSTM, accounts not only for the spatial dynamics- as in the other two models- but the temporal as well.

❖From Figure (5), the RC is predicting well up to approximately 100 days where it begins to diverge from the truth. One model time unit is 0.1121 days or 161.5 minutes. The histogram shows the Valid Prediction Time (VPT) which is the length of time the RMSE for a forecast stays below a threshold of ε= 0.2 or 20% [3]

Bibliography

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