Deep Regressor Chain: A Hybrid Approach for Long Term Time Series Prediction

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Water quality is an important issue because of its effects on human health and aquatic ecosystems. An understanding of the long term trends in water quality is extremely important for scheduling water quality management activities. Data-driven models have gained much attention for predicting nonlinear time series in hydrological modelling, yet predicting long term water quality change is still a big challenge.

Challenges for Predicting Time Series

Firstly, most of these studies are restricted to predicting water quality in one short upcoming time step. In this approach, hourly/daily predicative models only predict water quality in the next one hour/day, and provide no information on the longer-term trends in water quality.

Secondly, while some data-driven models can predict monthly or yearly water quality changes, they either use or resample the data with monthly or yearly time interval. Therefore, the 'long term' prediction still follows the one time step idea and has the same single prediction issue.

Deep Regressor Chain

We proposed a deep learning based method that we call Deep Regressor Chain (DRC) to overcome the above issues.

DRC connects multiple recurrent neural network (RNN) models in order. The 1st RNN uses N numbers of time series data and predicts at time step N+1. The 2nd RNN combines the previous RNN's inputs and prediction together as the new input to predict at time step N+2. Followed by this hybrid strategy, DRC can predict long term water quality in k upcoming time steps at once by integrating all the previous predictions and no extra water quality data resampling work is needed.

DRC Training

Training DRC is very efficient because each RNN regressor in DRC is training-independent. The training data sets and model programs can be scheduled into different HPC servers and there is no data exchange during training.

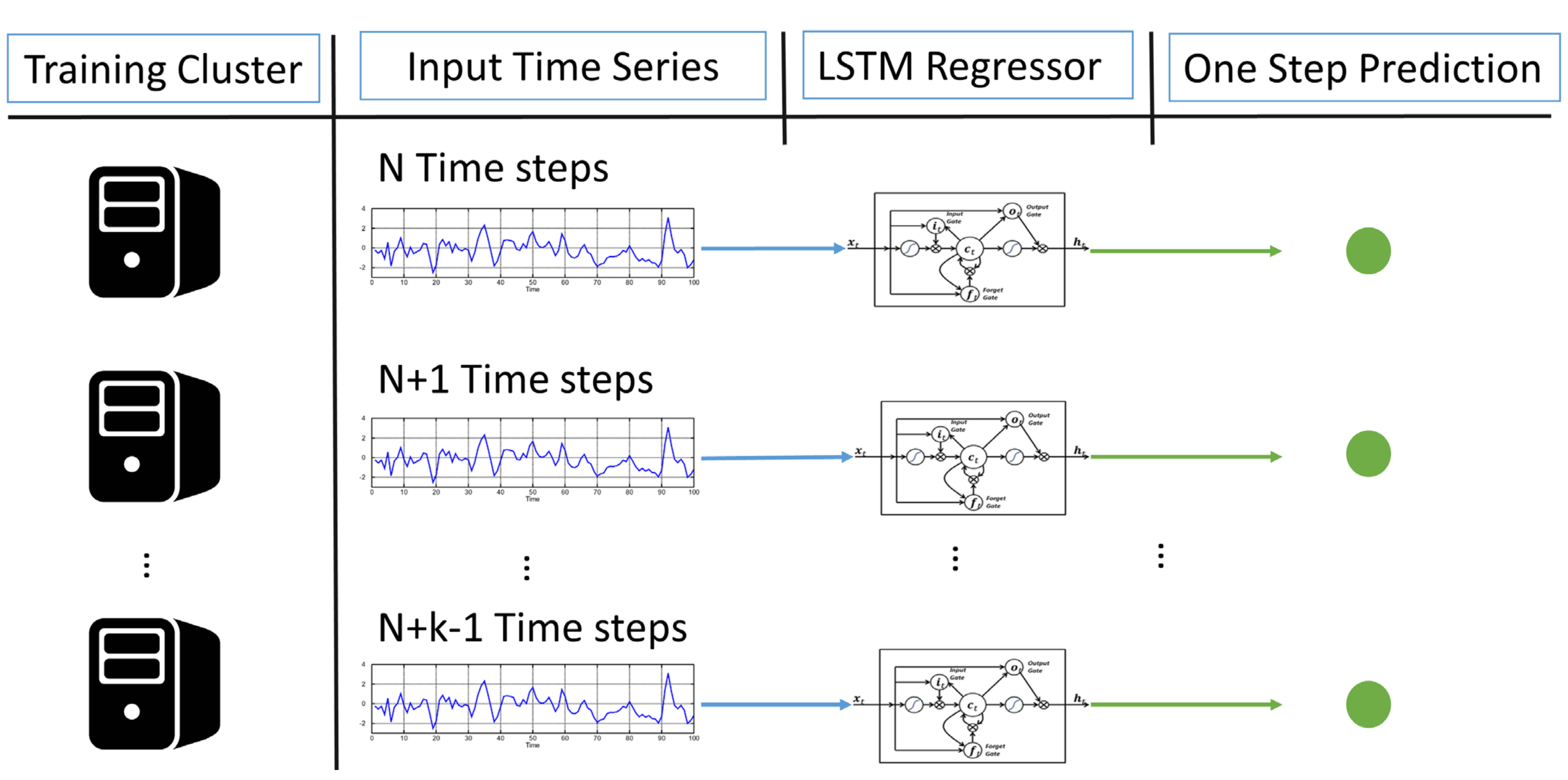

Figure 1: Parallel Training Each RNN Regressor in the HPC Cluster.

In Figure 1, for k time steps ahead predicting task, totally k number of LSTM regressors need to be built.

Each LSTM Regressor in the DRC is an one step predicting model. The 1st LSTM regressor accepts inputs with N time steps. Incrementally, the k-th LSTM regressor accepts inputs with N+k-1 time steps.

Hyperparameters for each LSTM regressor can be tuned independently and it makes us control the predictive accuracy for each time steps precisely.

DRC Predicting

For predicting, we sequentially connect each LSTM regressor and run the DRC model to get predictions for all upcoming time steps at once.

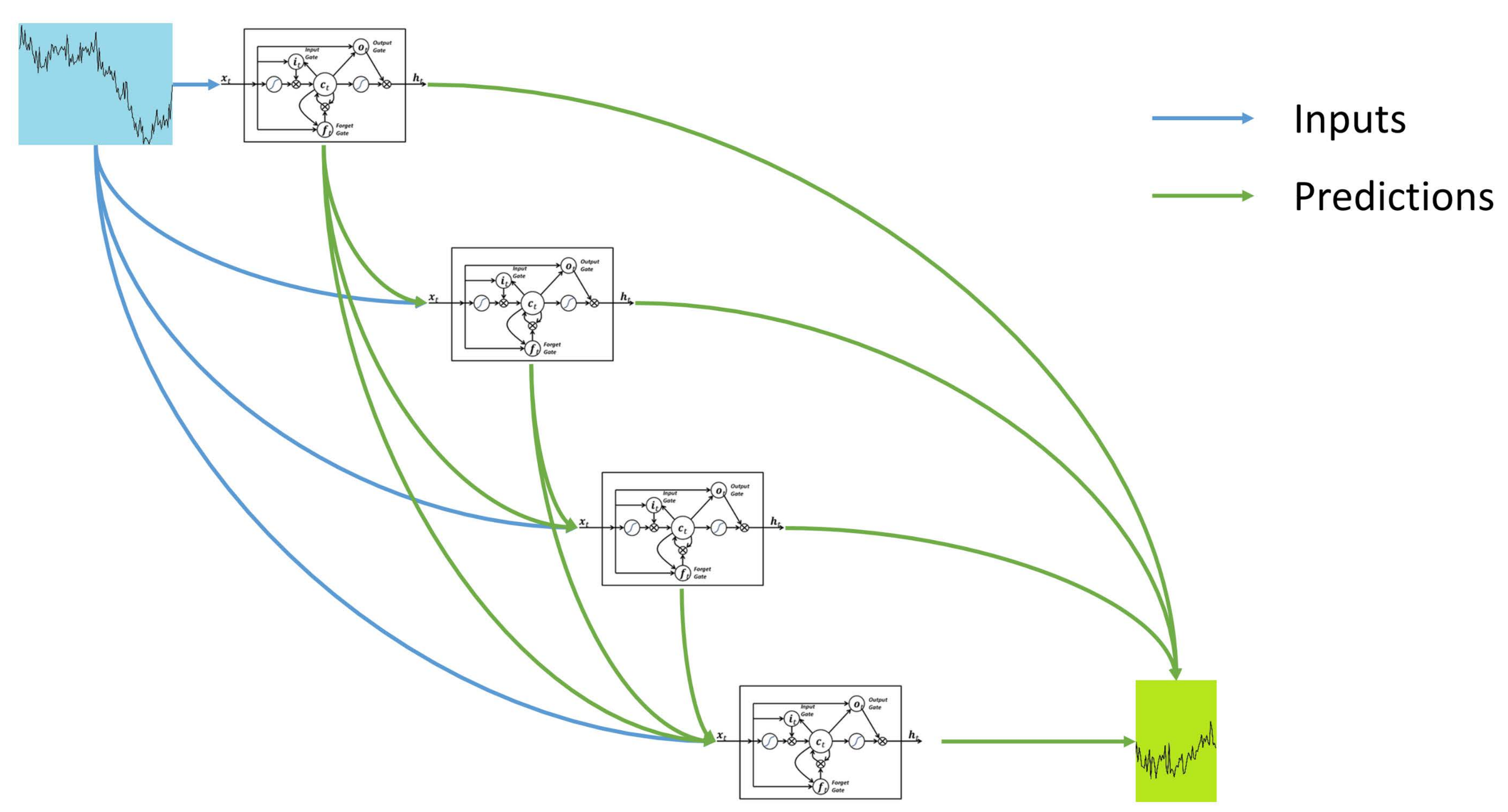

Figure 2: Sequential Predicting for Multi Time Steps by using DRC

In Figure 2, the DRC accepts the input time series data (blue time series) and feeds into the 1st LSTM regressor. The 1st regressor makes predictions on the 1st upcoming time step and combines the predictions (green flow) and origin inputs (blue flow) as the new inputs for 2nd LSTM regressor .

In DRC, each LSTM regressor keeps making predictions and passing updated inputs to the next LSTM regressor until k number of predictions are made. Then, the DRC will collect all the predictions made by each LSTM regressor and generate the final long term predictive time series (green time series)

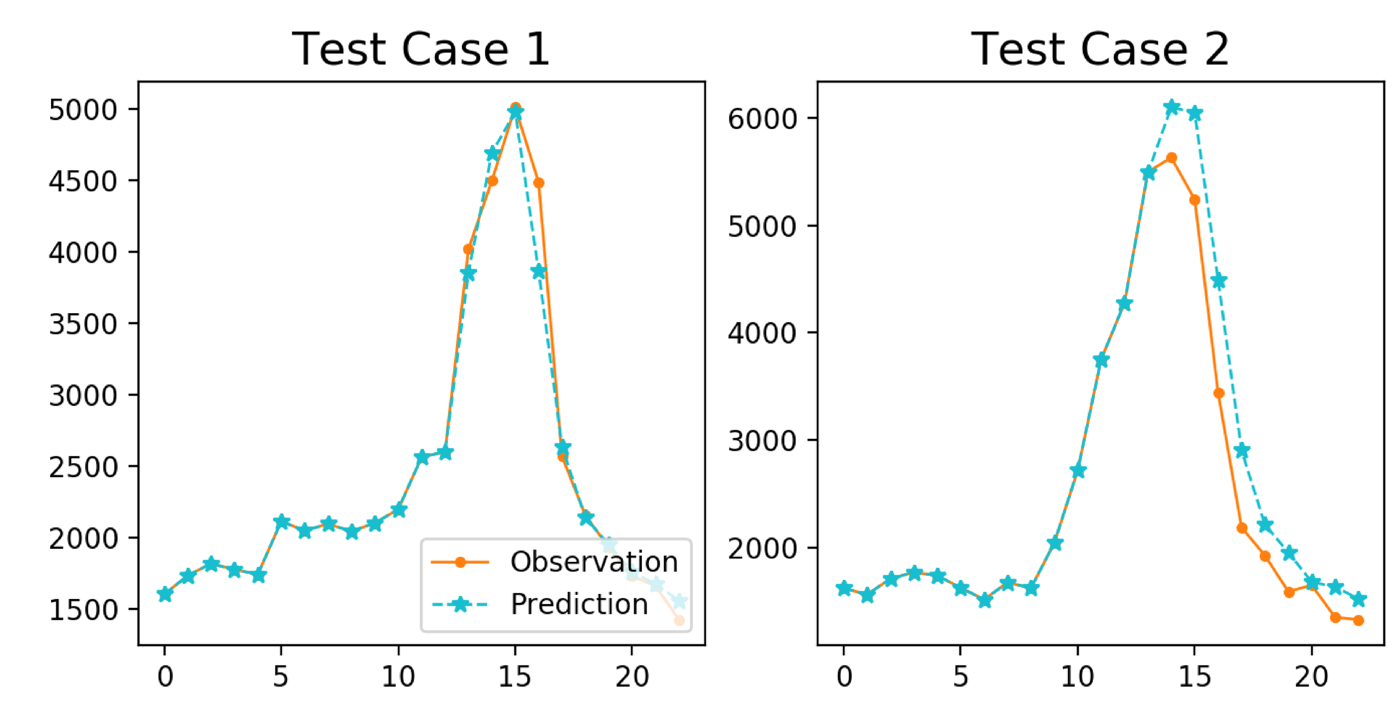

Figure 3: 10 Time Steps Predictions by using DRC

Figure 3 shows the results of predicting NDVI changes in 1100 locations, Australia. The DRC predicts the second half year's trend of NDVI based on the first half years NDVI time series data.

Conclusion

We design a deep learning model called DRC for predicting long term time series at once by integrating all the previous predictions. It is very efficient in distributed training and it is feasible for predicting in various upcoming time steps.

FOR FURTHER INFORMATION
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