Deep weather forecasting

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Abstract

As a natural consequence of the anthropocentric view of the reality, that pushed men to overproduction and the abuse of natural resources, we are now in an era where climate change becomes more dangerous and critical for the ecosystem safeguard and humanity survival. Finding a technique that predicts new trends and critical events – like thunderstorms or hurricanes – is essential to anticipate possible evacuation alarms, to prevent damage to objects and people and to optimize a system for green power generation.

In this project, I present a possible Deep Neural Network (DNN) technique which can be applied to weather forecasting. After a brief review of the state of art of this field, I show a different approach that is useful to predict time series of weather variables and classifications of critical events like storms and thunderstorms.

Weather Prediction Models (WPM) are based on a set of partial differential equations that takes in account of the most important physical processes that govern the atmospheric motions, discretizing the entire atmosphere field (global model) or part of this (local model) in a 3D grind. Running multiple simulations on supercomputers allows us to obtain a good weather forecast. But the complete prediction cycle is very computationally expensive and requires more time consuming data assimilation steps to correct prediction errors.

Artificial intelligence systems, in particular DNNs, are interesting tools that can learn how to resolve a required task by finding internal structures in the data used to train it. Image recognition, speech translation, smart recommendation and self-driving cars are only some of the applications that demonstrate the ability of these techniques and that they completely changed people's lives.

In the last 10 years, they are used also to predict weather events. In literature we can find different applications, from temperature to storms and precipitations predictions, that uses different architectures to forecast the variable of interest with interesting results. We can find fully connected neural network, or more sophisticate techniques that consider spatial [1] and spatiotemporal [2, 3, 4, 5] correlation or ensemble neural network approach [6]. But the most interesting and complete work in these field, in particular for these analysis, is a new approach based on Generative Adversarial Network (GAN) [7]. In this work, Ravuri et al. used a GAN to generate radar images for precipitation nowcasting that overcome the most powerful forecasting technique.

In the wake of these paper that I found in literature, I propose to study the forecasting of a DNN that combines the capacity to find a spatial correlation of a Convolutional Neural Network (CNN) with the ability to find temporal pattern, which is typical of the Recurrent Neural Network (RNN), using an architecture that deeply combines these two structures, while most of the works mentioned only concatenate CNN and RNN sequentially. If we incorporate the spatiotemporal dependence directly in the nets, it is potentially possible to obtain optimal forecasting of temporal series and a classification of critical behaviors, by simply changing the last layer, or combining multiple output layers in a multi-learning scheme.

The use of CNN in this kind of works can help the forecasting in case of missing values. In fact, studies in computer vision field, show that it is possible use CNN to correct images with burn or missing pixels, so we can hope to use the same effect to interpolate values of measures or using sequences derived from different stations situated in different places to obtain a spatially extended forecasting.

In my master's thesis, I have also studied the ability of a DNN, with and without memory, to forecast time series obtained from chaotic dynamical systems, especially using the Lorenz 63 model as toy model. I have also found out that it is possible to improve the prediction if we use synchronization techniques: if some measures are available, we can combine them with the output of the nets to improve the forecasting and the learning process.

References

- [1] Shreya Agrawal et al. "Machine learning for precipitation nowcasting from radar images". In: *arXiv preprint arXiv:1912.12132* (2019).
- [2] SHI Xingjian et al. "Convolutional LSTM network: A machine learning approach for precipitation nowcasting". In: Advances in neural information processing systems. 2015.
- [3] Casper Kaae Sønderby et al. "Metnet: A neural weather model for precipitation forecasting". In: arXiv preprint arXiv:2003.12140 (2020).
- [4] David Kreuzer, Michael Munz, and Stephan Schlüter. "Short-term temperature forecasts using a convolutional neural network—An application to different weather stations in Germany". In: *Machine Learning with Applications* (2020).
- [5] Zao Zhang and Yuan Dong. "Temperature forecasting via convolutional recurrent neural networks based on time-series data". In: *Complexity* (2020).
- [6] Imran Maqsood, Muhammad Riaz Khan, and Ajith Abraham. "An ensemble of neural networks for weather forecasting". In: *Neural Computing & Applications* (2004).
- [7] Suman Ravuri et al. "Skillful Precipitation Nowcasting using Deep Generative Models of Radar". In: *arXiv preprint arXiv:2104.00954* (2021).