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# The adoption of Deep Learning in Weather Forecast

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Technological development and the internet of things (IoT) increased the data assimilation sources in meteorology through satellites, sensors, weather stations, solar panels, cell phones, traffic lights, to name a few whose number grows daily. This begins to build an ideal scenario for Artificial Intelligence where the demand for data is high. This combined information generates spatio-temporal maps of temperature, rainfall, air movement, etc., with high precision in regions with larger data sources. Applying AI techniques in conjunction with a physical understanding of the environment can substantially improve prediction skill for multiple types of high-impact weather events.

In 2017, the American Meteorological Society (AMS) published a paper [1] with a broad summary indicating how modern AI techniques are helping to improve insights and make decisions in weather prediction. Among the most used techniques are Support Vector Machines (SVM), regression trees, k-means for radar image segmentation and traditional neural networks (ANN). These techniques lack temporal and spatio-temporal analysis, typical of meteorological phenomena. Today, most of the temporal analysis done on meteorological data is through statistical algorithms, such as autoregressive methods. However, the AMS recognizes that the novel Deep Learning techniques could soon be the cause of new improvements and says, "In the future, convolutional neural networks operating in a deep learning framework may reduce the need for feature engineering even further" .

Complementarily, recurrent neural networks, designed for analysis of natural language processing, are known by their results in numerical problems like temperature prediction, among others. In order to improve the temporary forecasts of spatio-temporal phenomena, such as rain and temperature, hybrid architectures have emerged that build the temporary forecast coding the spatial pattern of the neighborhood.

In [7], Shi et al. formulate precipitation nowcasting as a spatio-temporal sequence forecasting problem in which both the input and the prediction target are spatio-temporal sequences. They extend the fully connected LSTM (FC-LSTM) to have convolutional structures in both the input-to-state and state-to-state transitions, they propose the convolutional LSTM (ConvLSTM) and use it to build an end-to-end trainable model for the precipitation nowcasting problem. Experiments show that the ConvLSTM network captures spatio-temporal correlations better and consistently outperforms FC-LSTM and the state-of-the-art operational ROVER algorithm for precipitation nowcasting.

In [8], Souto et al. use a ConvLSTM architecture as a spatio-temporal ensemble approach. The channels in the convolution operator are used to input different physical weather models. In this way the ConvLSTM encodes the spatial information which are subsequently learned by the recurrent structures of the network. The results show that ConvLSTM achieves superior improvements when compared to traditionally used ensemble techniq ues such as BMA [9].

As a matter of fact, there are a plethora of opportunities to be investigated extending the initial results we have achieved in adopting Deep Neural networks to weather prediction. Linear and causal convolution operators (the latter also known as temporal convolution), for instance, have resulted in deep networks architectures that use convolutions to encode and decode time and space with greater precision. Raissi and colleagues [10] investigate the integration of physical laws described as a set of partial differential equations to the training process. By means of such integration, the training process is bound to obey the physical laws, an approach that has been dubbed as model teaching . Another area of interest is multimodal machine learning (MML) [11]. In MML, data from different representations are complementarily used in building models, including: images; textual data; quantitative dataetc… This can be extremely interesting in weather forecast as more data is captured from satellite images and sensors data to weather bulletins and predictive physical models.

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## Supported Student

**Primary author:** Dr MOLINA SOUTO, Yania (LNCC)

**Co-author:** Dr PORTO, Fabio (LNCC)

**Presenter:** Dr MOLINA SOUTO, Yania (LNCC)

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