Offre de stage :

Rain Nowcasting using convolutional-reccurent neural networks

Niveau : M2

Cadre :

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- Laboratoire : LIP6

Durée et Période : 5/6 months from March 2020

Lieu : 4 Place Jussieu, Paris, France

Contexte scientifique :

Precipitation forecasting at a short and mid-term horizon, also named rain nowcasting, is a complicated problem in Numerical Weather Prediction due to the high non-stationarity of the rain processes. Real life applications for example address severe events anticipation [1] (short term horizon, lower than 2 hours) or agriculture management [2] (longer horizon, up to 4 hours). Traditionally and in operational center, forecasts are produced based on the combination of physics-based numerical models and observations (e.g. from radar, satellite), this method is called Data Assimilation [3, 4]. Basically, it estimates the motion field in order to advect observed storm cells. But the creation/dissipation process of these cells is not well understood and hard to model. However, over the past decade, Machine learning and more precisely Deep Learning have shown great abilities to model complex spatio-temporal dependencies [5] that usually require the use of differential equations. We aim at comparing traditional methods with fully data-driven ones and eventually combining them.

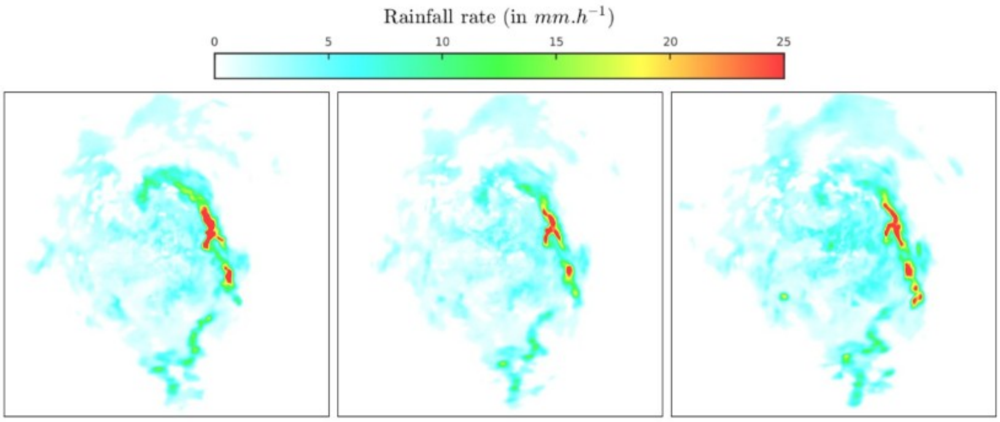

Fig 1: Example of three successive Radar acquisitions of precipitations.

Objectifs :

The main goal of the internship is to learn a model on rainfall records provided by the Météo France radar network (e.g. PANTHERE data). Even though we may try different architectures, we are particularly interested in convolutional-recurrent networks presented in [6, 7] as they are primarily applied on rain nowcasting. Indeed, dealing with rain data could be sensitive as precipitation measures are sparse in space and time. We should define an evaluation procedure to first select our learned networks and then comparing them to variational data assimilation methods already available, criterion can be multiple.
In a second step and depending on the results, we would try to incorporate physical knowledge into our model which is a relatively open topic [8, 9, 10]. We could consider hybrid modelling within a variational data assimilation scheme [11, 12] connecting the work of a phd student.

Références bibliographiques :

[1], Joe et al, 2012, Automated processing of doppler radar data for severe weather warnings, In book: Doppler Radar Observations - Weather Radar, Wind Profiler, Ionospheric Radar, and Other Advanced Applications

[2], Stigter et al, 2000, Agrometeorology in the 21st century: workshop summary and recommendations on needs and perspectives, in Agricultural and Forest Meteorology, 103(1/2):209–227

[3], Marc Bocquet, 2018, Introduction to the principles and methods of data assimi-
lation in the geoscience, Lecture notes

[4], Bereziat et al, 2018, Motion and acceleration from image assimilation with evolution models, in DSP

[5], He et al, 2015, Deep Residual Learning for Image Recognition, arXiv

[6], Shi et al, 2015, Convolutional LSTM Network: A Machine LearningApproach for Precipitation Nowcasting, arXiv

[7], Shi et al, 2016, Deep Learning for Precipitation Nowcasting: A Benchmark and A New Model, arXiv

[8], Karpatne et al, 2016, Physics-guided Neural Networks (PGNN): An Application in Lake Temperature Modeling, arXiv

[9][Reichstein et al, 2019], Deep learning and process understanding for data-driven Earth system science, Nature

[10], De Bézenac et al, 2017, Deep Learning for Physical Processes: Incorporating Prior Scientific Knowledge, arXiv

[11], Bocquet et al, 2019, Data assimilation as a learning tool to infer ordinary differential equation representations of dynamical models, in Nonlin. Processes Geophys. Discuss

[12], Brajard et al, 2019 Combining data assimilation and machine learning to emulate a dynamical model from sparse and noisy observations: a case study with the Lorenz 96 model, in Nonlin. Processes Geophys. Discuss

Compétences souhaitées :

- Machine Learning, Deep learning, Signal processing, Data Analysis
- Python programming, Pytorch is a plus
- Interest for climate applications

Autres : the intern will have the opportunity to participate in AI4C / SCAI seminars