Use of IA for MJO diagnostic in monthly forecasts

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Introduction

Background :

- S2S forecasts: Subseason to seasonal → 2 weeks to 2 months
- Cyclonic activity on the SWIO basin: MJO and equatorial waves
- MJO forecasts from week 1 to week 4 : amplitude and phase
- 6-month internship project from Remy Köth within the PISSARO project

Objective : assessing the potential of machine learning (ML) methods to determine MJO, by post-processing a S2S model

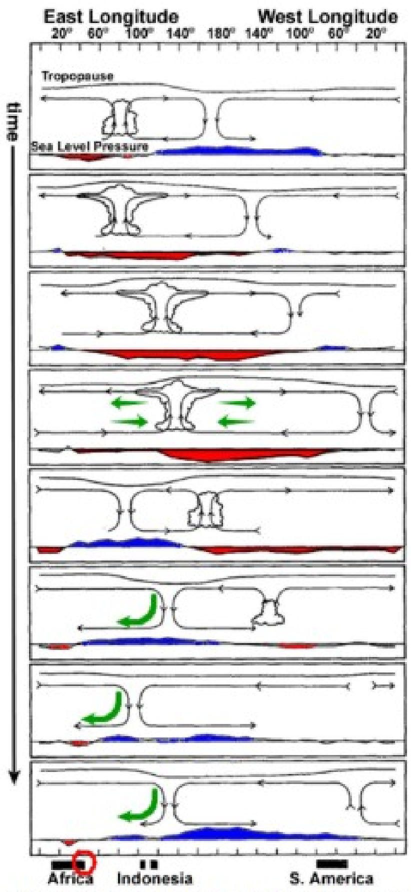
- Several regression models
- In analysis mode (ech 0)
- In forecast mode

Exploration of an approach based on processing past RMM time series

Outline

- Scientific context
- Data
- Methods
- Results
- Conclusion and perspective

Background – Madden-Julian Oscillation (1)



Source : cours de Frédéric Ferry, d'après [Madden and Julian, 1971]

- Main variability mode of the atmosphere at subseasonal scale in the tropics
- Slow eastward propagation : period from 30 to 80 days
- Active phase : deep convection anomaly
  - Low pressure anomaly at sea level
  - Zonal wind convergence anomaly in lower levels and divergence anomaly in upper levels
- Inactive phase : large scale subsidence anomaly
  - High pressure anomaly at sea level
- Variation of intensity for each MJO episode

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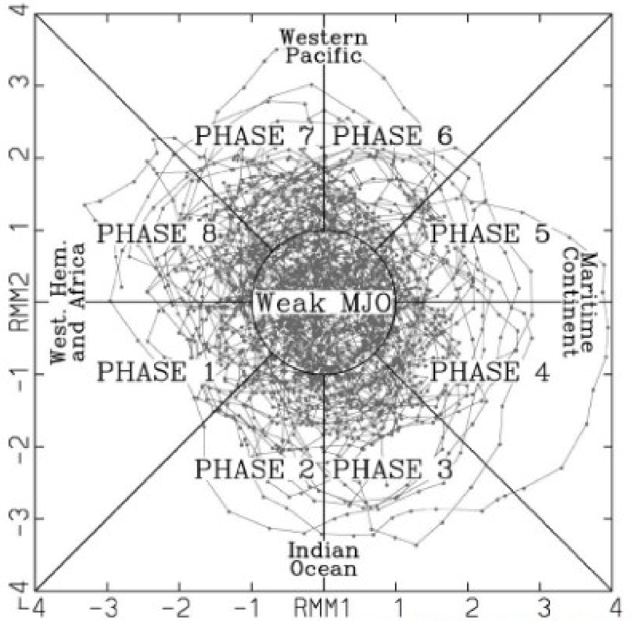
Background – Madden-Julian Oscillation (2)



Source : [Wheeler and Hendon, 2004]

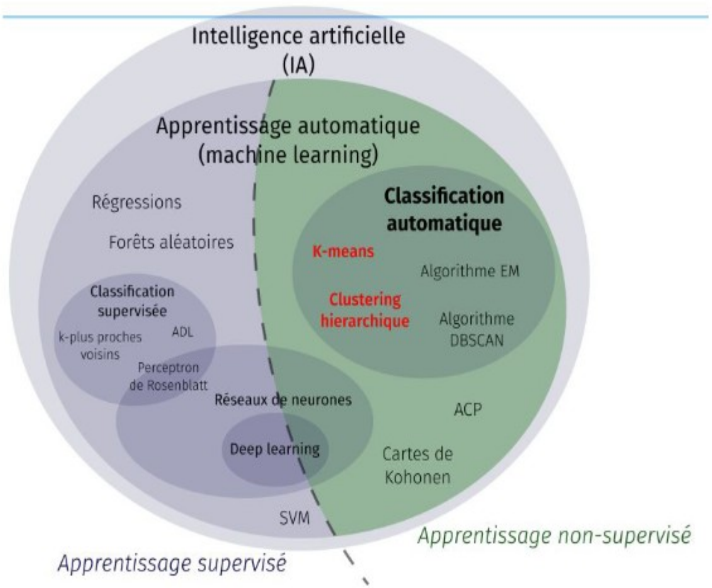
Source : cours de Nicole Girardot

- Caracterization of MJO with RMM indices
- Imperfect diagnostic of MJO but used here as « ground truth »

- Built on Principal Component Analysis on 3 2D-field :
  - OLR : Outgoing Long Range (W.m^{-2})
    - Infrared emission from the atmosphere
      - Low OLR → low temperature → high level clouds → deep convection
  - U850 : 850-hPa zonal wind (lower levels)
  - U250 : 250-hPa zonal wind (upper levels)
- RMM1 and RMM2 : the 2 first principal components
- Position in phase space characterizes:
  - MJO Intensity: non intense within the central circle
  - MJO phase: position on the globe

Background: Artificial Intelligence

Machine learning: Use of statistical methods to build a prediction model by learning on a dataset without expert knowledge



Source : cours de Thomas Rieuutord

- Supervised learning vs unsupervised
- Neural Network and deep learning
- For supervised learning :
  - Training on a train set
  - Evaluation on a test set
- Regression of RMM indices from Numerical Weather Prediction (NWP) outputs

Data

- Output: RMM indices from the Bureau of Meterology (BoM, Australia)
  - 1 index per day from 1974 until now
  - OLR : satellite observations from NOAA
  - U250 and U850 : reanalyses from NCEP
- Features: ECMWF ensemble model
  - Real-time and reforecast → homogeneous data on CY46R1 version
  - Period from 2000 to 2019. Train set: 2000-2014. Test set : 2015-2019
  - 2 runs per week→ 1575 samples in train set. 525 in test set.
  - Lead time from 0 to 32 days with 1-day timestep
  - Domain : 30°N-30°S for all longitude
  - Resolution : 1.5° x 1.5° horizontal grid for all vertical levels
  - Ensemble : 1 control member and 10 perturbed members
  - Parameters : OLR, U850, U250, TCW, past RMM indices

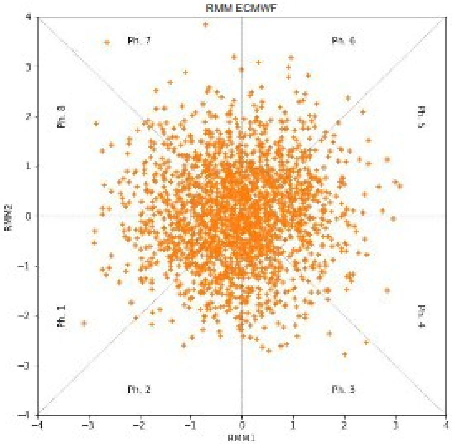
Methods

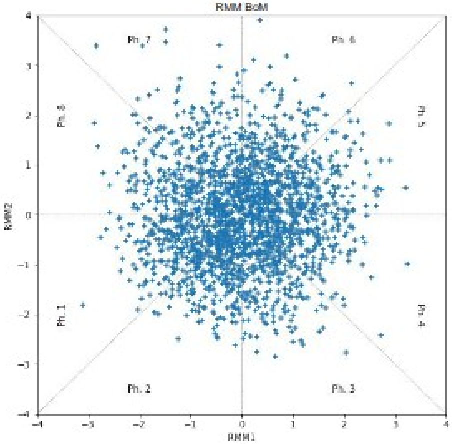
Machine learning methods :

- Linear regression
- Support Vector Regression : → non linearities
- Neural network : Multi Layer Perceptron (MLP)
- Convolutional Neural network → spatial information
- K-Nearest Neighbour (k-NN) and random forests

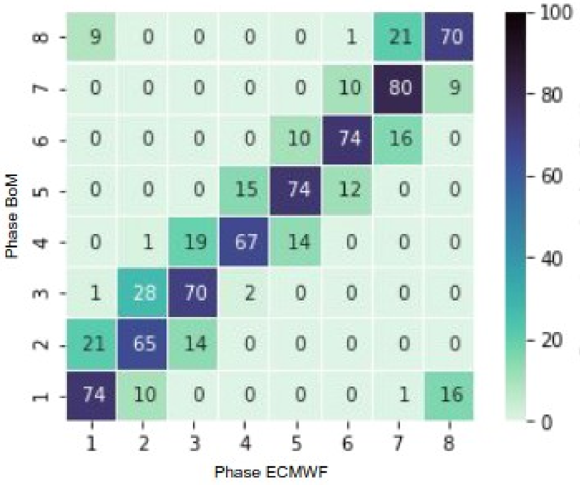
Evaluation with multiple scores

Results - Analysis mode - Reference



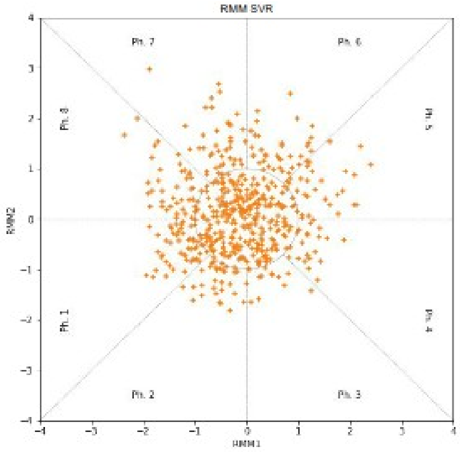


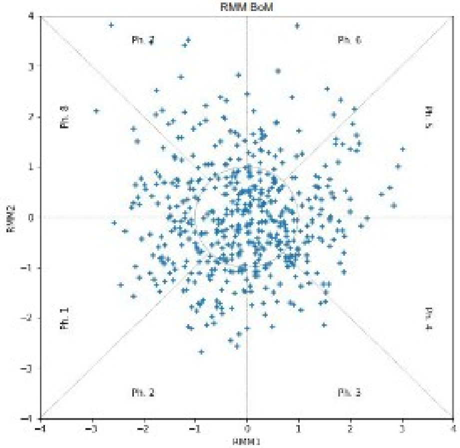
	Ref	SVR
Non intenses identifiés	78%	
Intenses identifiés	82%	
Précision	72%	
Précision à une phase près	99.6%	



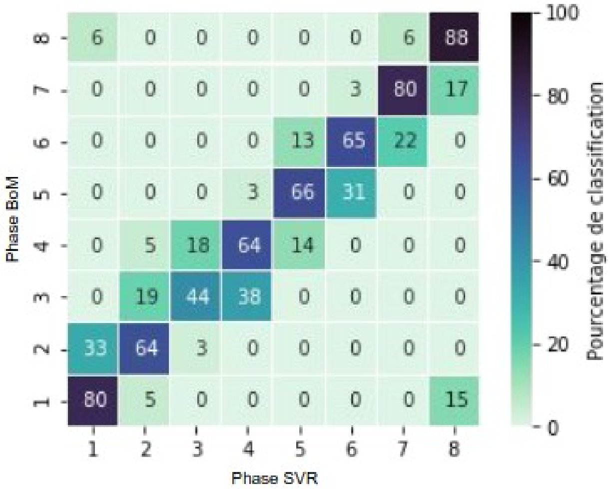
	Ref	SVR
MAE (mean absolute error)	0.33	
MSE (mean squared error)	0.18	
Distance euclidienne	0.52	
BRMSE (bivariate root mean squared error)	0.60	
BCORR (bivariate correlation)	0.91	
Erreur amplitude	-0.05	
Erreur absolue amplitude	0.30	
Erreur angle	-2.8°	
Erreur absolue angle	21°	

Results - Analysis mode – Support Vector Regressor



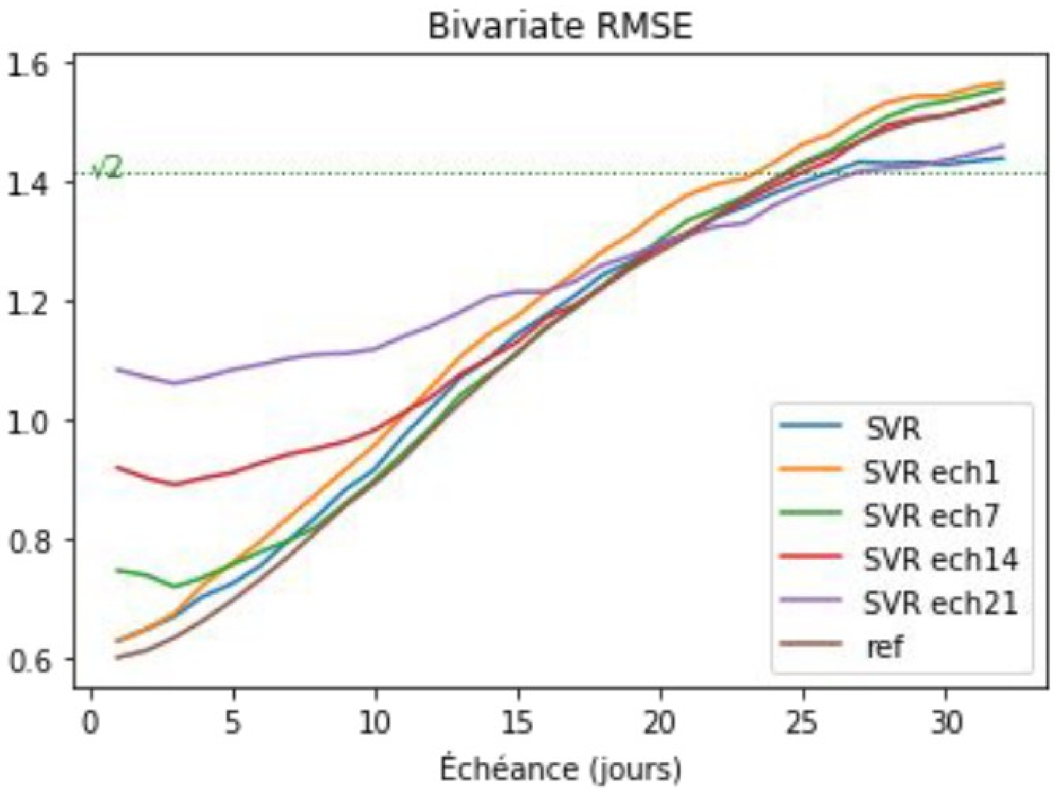


	Ref	SVR
Non intenses identifiés	78%	89%
Intenses identifiés	82%	71%
Précision	72%	71%
Précision à une phase près	99.6%	99.4%



	Ref	SVR
MAE (mean absolute error)	0.33	0.38
MSE (mean squared error)	0.18	0.22
Distance euclidienne	0.52	0.59
BRMSE (bivariate root mean squared error)	0.60	0.66
BCORR (bivariate correlation)	0.91	0.91
Erreur amplitude	-0.05	-0.27
Erreur absolue amplitude	0.30	0.40
Erreur angle	-2.8°	0.60°
Erreur absolue angle	21°	22°

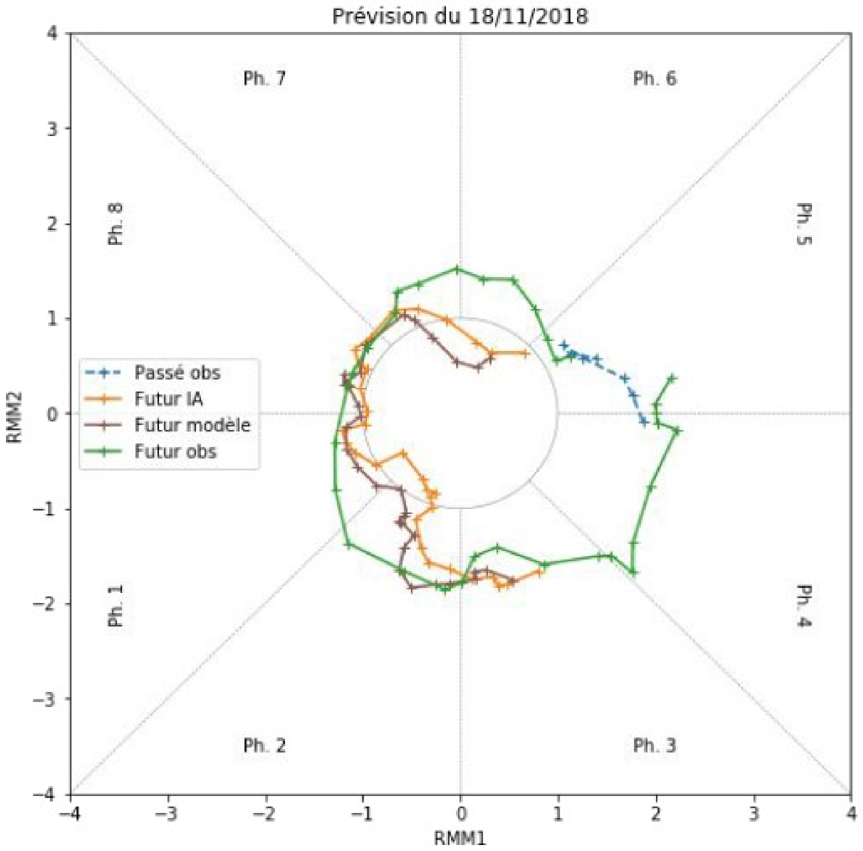
Results – forecast mode



- Model trained with different S2S model lead times as inputs
- SVR ech21 improves forecasts from D+21
- Previsibility :

  D+24 (ref) → D+26 (ech 21)
- Improvement of other scores at shorter lead time

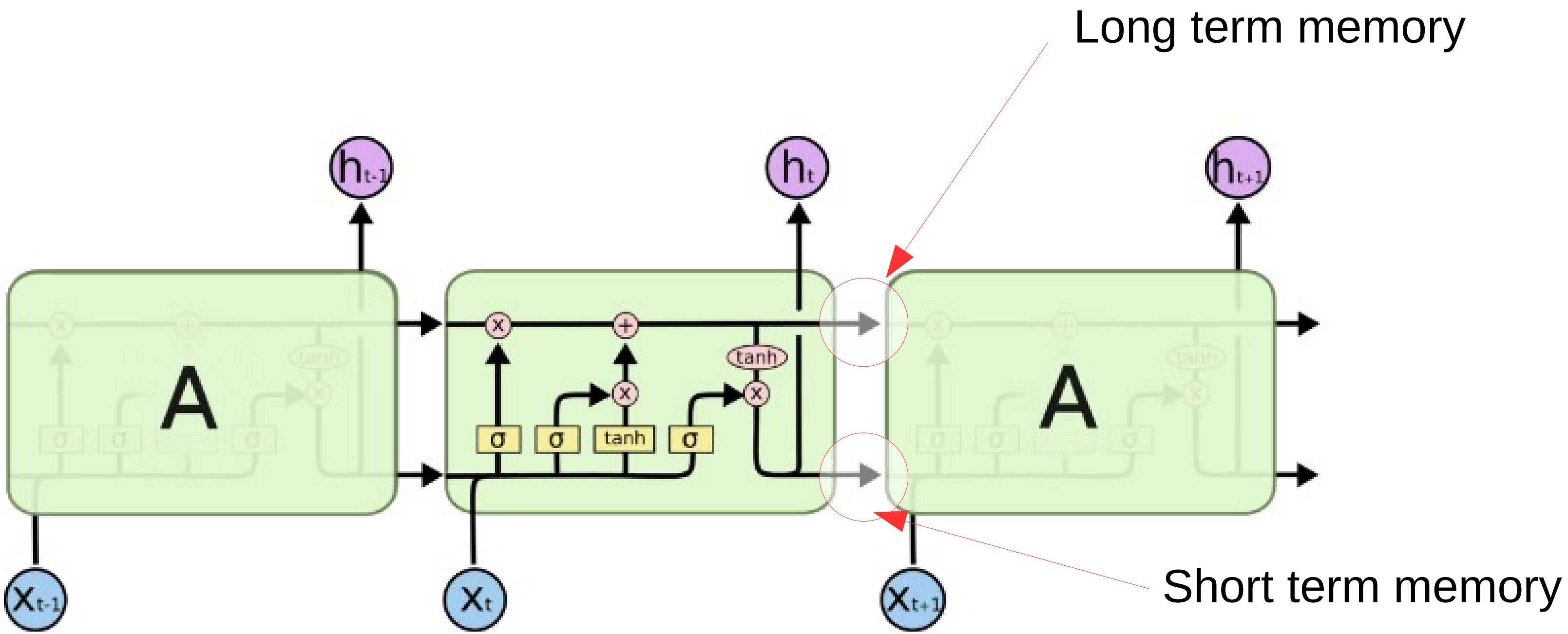
Example on a MJO event



Extracting information from MJO propagation - Recurrent Neural Network

- Inputs : time serie of past RMM indices
- Outputs : time serie of future RMM indices
- Pre-processing : 7-day moving average of the time series
- RNN (based on LSTM cells) useful for predictions from time serie
- Post-calibration of predicted MJO amplitude

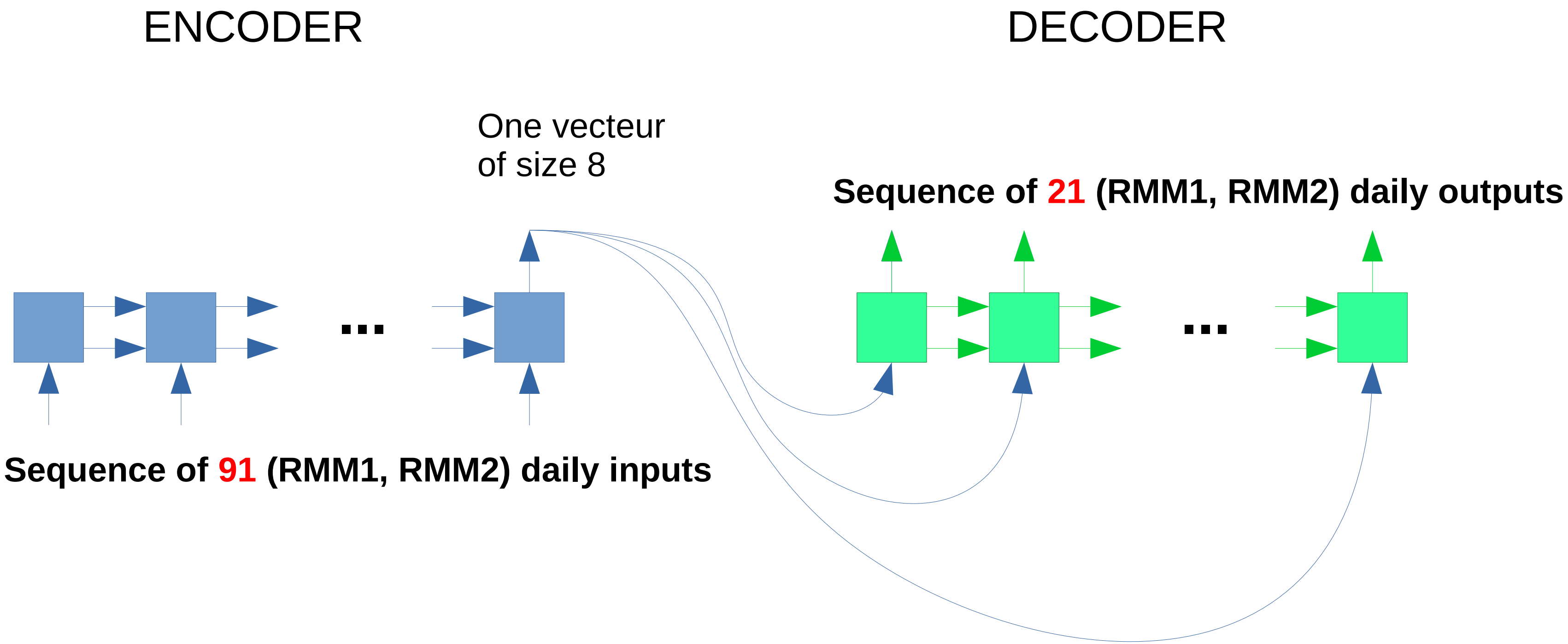
Description of a Long-short Term Memory (LSTM) cell



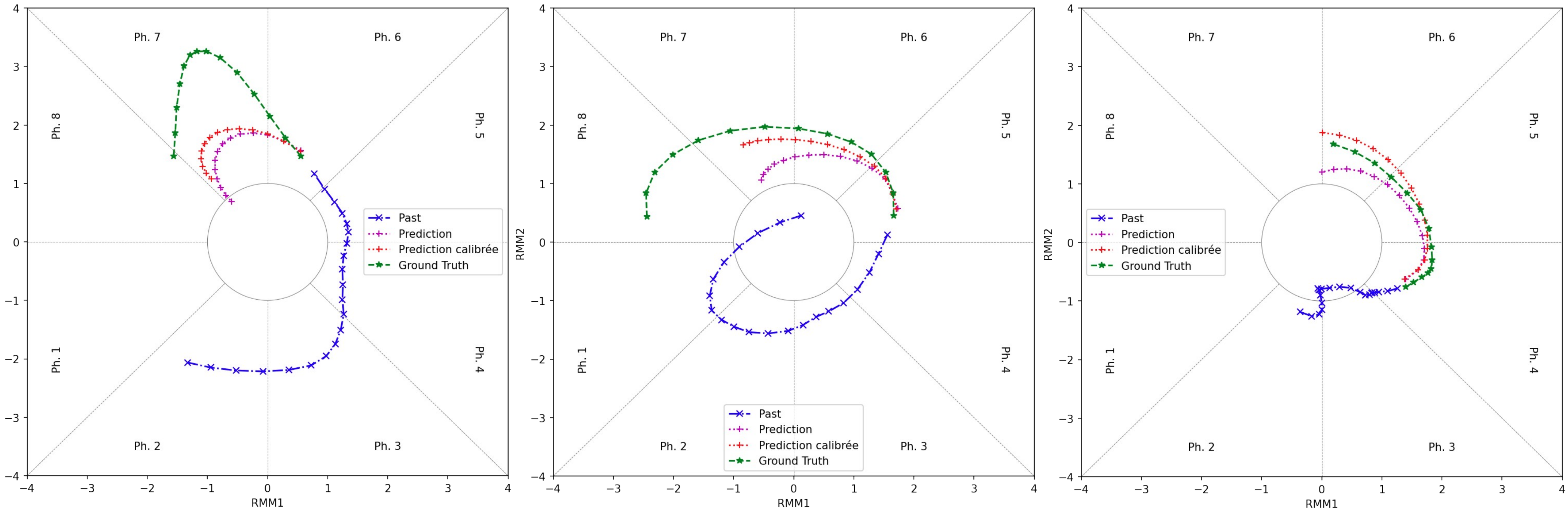
The repeating module in an LSTM contains four interacting layers.

Source : Understanding LSTM Networks, 2015

Global Neural Network architecture



2-week forecast examples



Accurate phase but weak amplitude for MJO prediction

Fair amplitude but phase delay for MJO prediction

Amplitude and phase prediction consistent with ground truth

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Conclusions and perspectives

- Main results from Remy's project :
  - In analysis mode :
    → ML able to emulate the RMM calculations and at the same time unbias the S2S model
  - In forecast mode :
    → forecast improvement with a MJO previsibility extention of 2 days
- RNN can predict future RMM from past RMM time serie
- Importance of pre and post processing for improving predictions based on ML
- Potential for machine learning to extract useful information and optimize MJO prediction from multiple data sources
- Interest for processing the incertainty from the ensemble forecast