Machine Learning Lifecycle for Earth Science Application: A Practical Insight Into Production Deployment

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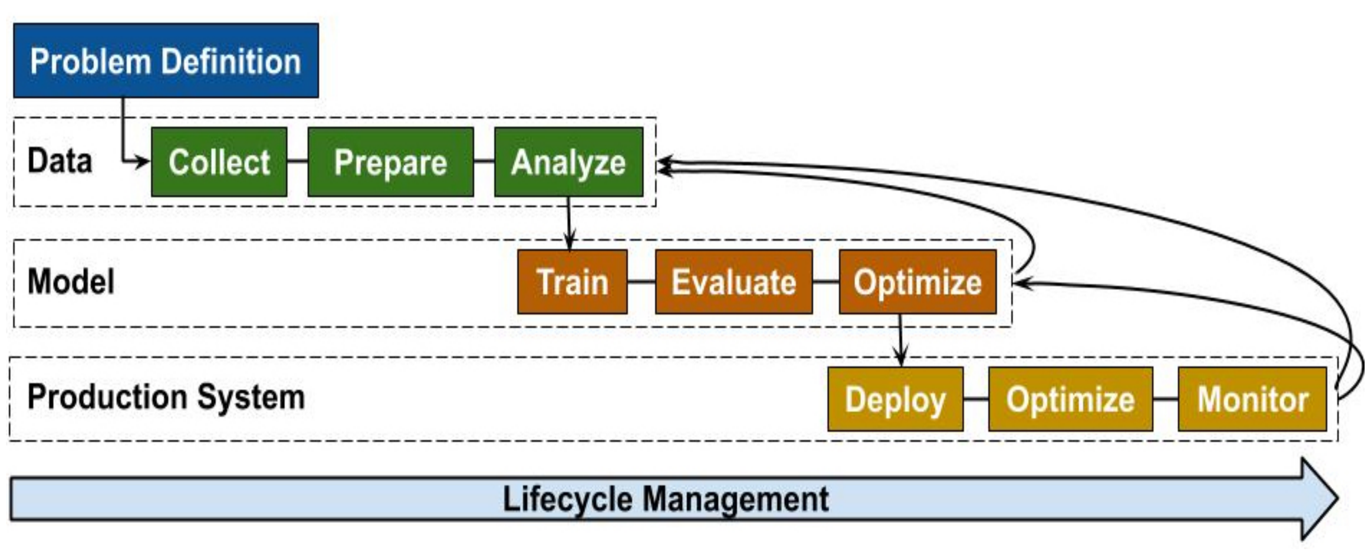
Introduction

Earth science domain presents unique sets of problems that are increasingly being solved using data driven approaches. The availability of big Earth science data offers immense potential for Machine learning (ML) as evident from numerous research publications lately. However, many of these publications are not ending up as production applications mainly because the data scientists who develop the ML models are now expected to complete the ML lifecycle by deploying and scaling the models in production.

We introduce ML lifecycle to the Earth science community including the opportunities and challenges that lie ahead in each phase of the lifecycle. We demonstrate the lifecycle using an Earth science problem that we used ML to address and transitioned to production.

Machine Learning Lifecycle



Problem Definition

Objectively estimate tropical cyclone wind speed using just satellite images

Data Collection and Analysis

Collect, prepare, and analyze the data required to test the hypothesis.

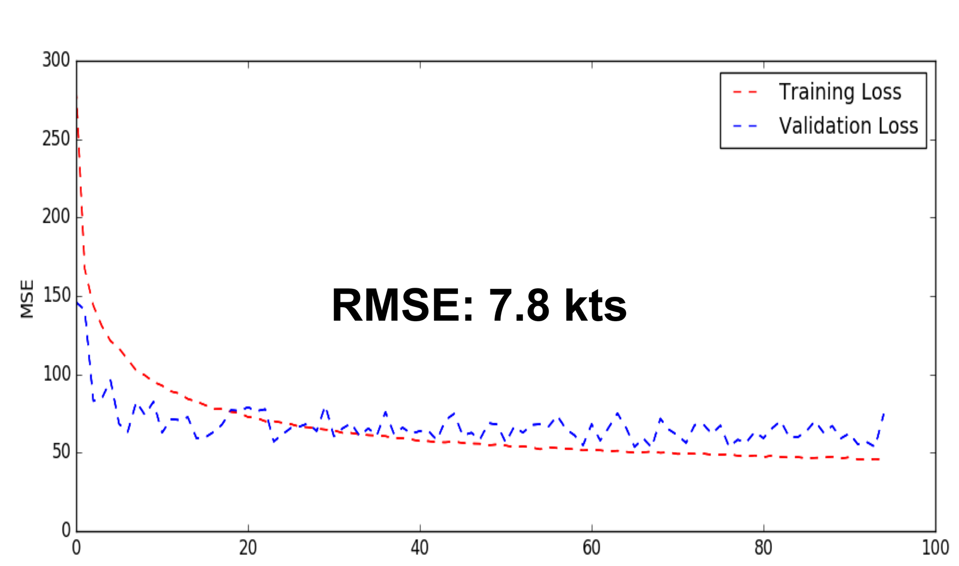
Initial training image dataset constructed using satellite images from U.S. Naval Research Laboratory (NRL)

- *IR images are captured around fifteen minutes apart*
- *In production: NRL image database was not sufficient and required more samples at higher temporal frequency.*
- *For production, in real-time same preprocessing steps do not apply in generating images.*
- *Transitioned to raw GOES-R data available from NOAA's CLASS and wind speed information from HURDAT2*

Model Development and Evaluation

Pick an algorithm suited to test the hypothesis and train a model , evaluate the model, iteratively refine the data and model

- *New data and initial model: RMSE of 10.18 knots*
- *Modified CNN model architecture using a custom loss function by incorporating mean squared error (MSE) between actual wind speed of the image being used against the estimated wind speed.*



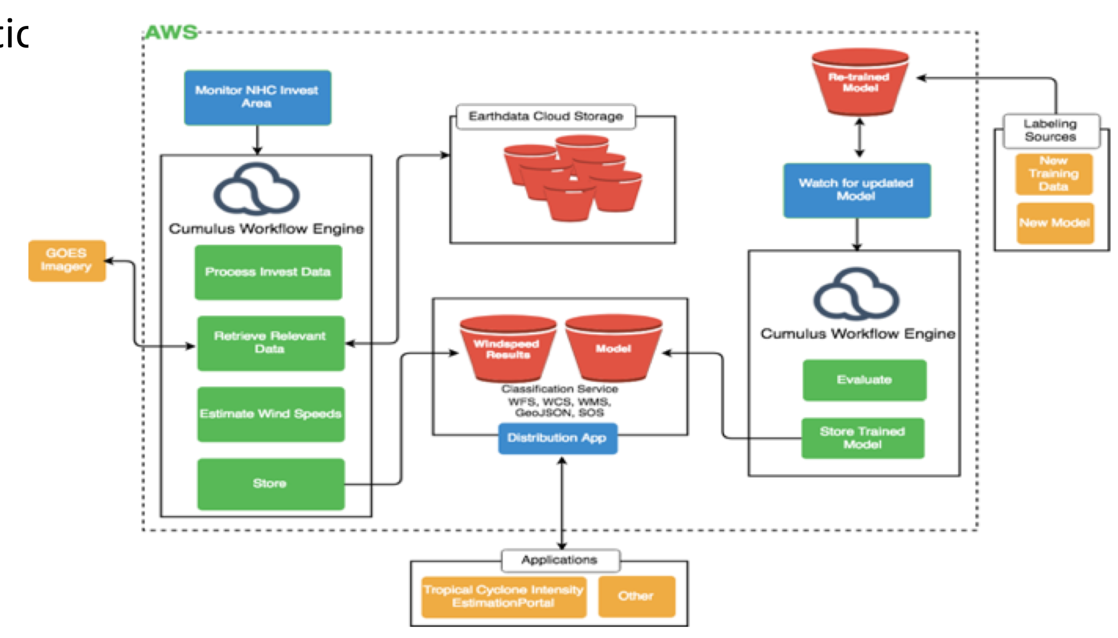
Model performance in production

Production System Deployment

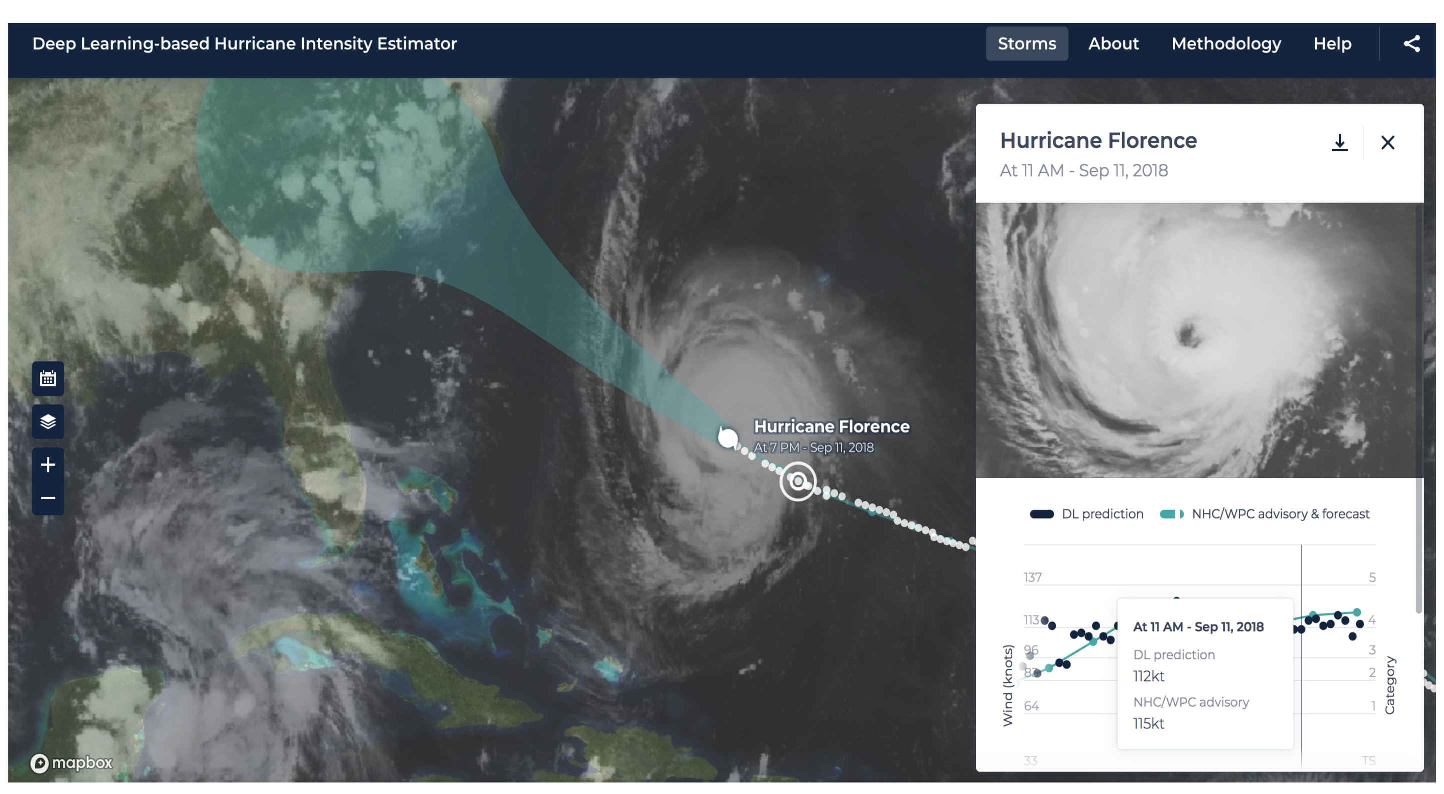
Evaluate the model's performance in production, collect and store additional data from user interactions, plan retraining frequency, understand data preprocessing needs, identify performance requirements in production, develop metrics and baselines with initial model, monitoring over time, back-test and now-test.

Tropical Cyclone Intensity Estimation Portal (TCIEP):

A. Monitor NHC outlook for "invest" area for trigger
B. Near real-time tropical cyclone intensity estimation services
C. Map display
D. Relevant layers
E. Comparison with operational forecasts
F. Evaluatic

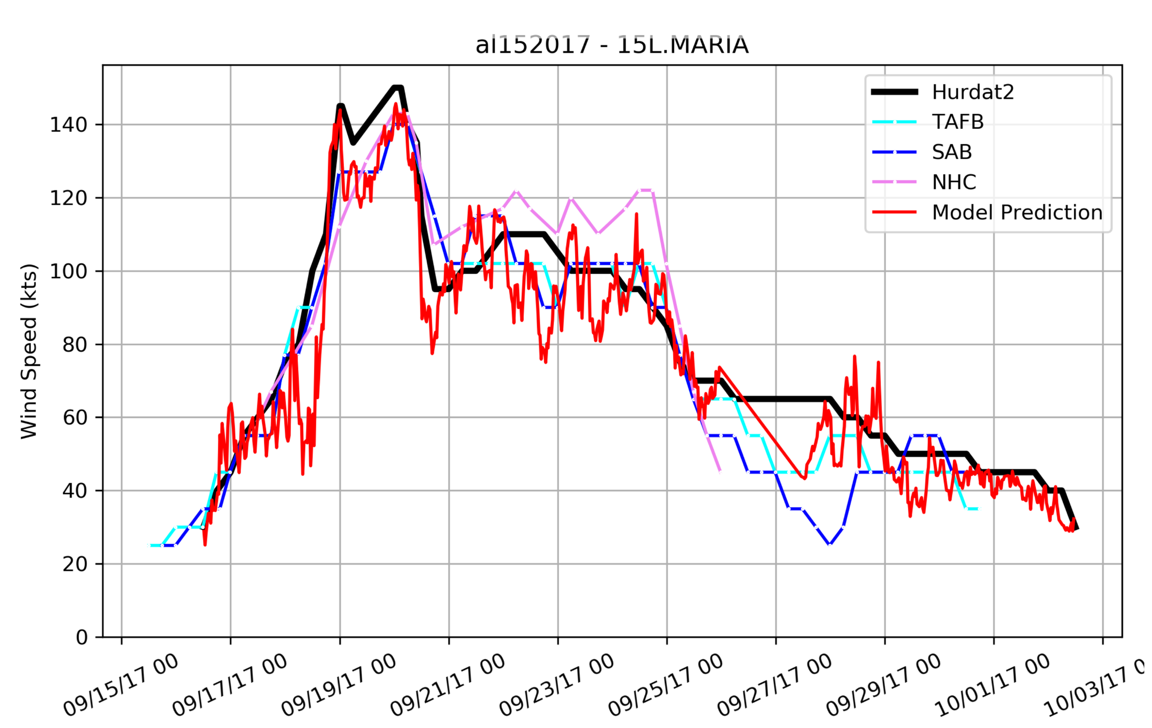


AWS cloud based architecture for tropical cyclone intensity estimation portal



http://hurricane.dsig.net

Tropical cyclone intensity estimation portal



Comparison of production model's estimation with existing methods using 2017 hurricane Maria

Challenges and Lessons Learned

A. Tracking changes
B. Measuring the accuracy of the model
C. Collecting and act on user feedback for improvements
D. Syncing data (source, training, and result), code (algorithm, model, deployment), model-specific parameters and environments, and platforms is also very challenging.
E. Interpreting of ML output
F. Keeping up with the complexities associated with evolving platforms and infrastructure
G. Communicating across teams of ML experts, domain scientists, software engineers, UI designers, and software architects
H. Complexity with evolving platforms and infrastructure

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