



Engineering, Test & Technology
Boeing Research & Technology

Challenges identified in the SESAR ER: DART project

Pablo Costas, Javier Lopez— Boeing Research & Technology Europe

DART in a nutshell

DART (Data-driven AiRcraft Trajectory prediction research) addresses the topic “**ER-02-2015 - Data Science in ATM**” exploring the applicability of **data science** and **complexity science** techniques to the ATM domain. DART delivers an understanding on the suitability of applying big data and agent –based modelling techniques for predicting aircraft trajectories based on data-driven models and accounting for ATM network complexity effects, considering multiple correlated trajectories.

DART focused on answering following questions:

- What are the supporting data required for accurate trajectory predictions?

Flight plan, weather, surveillance, airspace (sectors, regulations, RADs) and intent (derived)

- What is the potential of machine learning algorithms to support high-fidelity aircraft trajectory prediction?

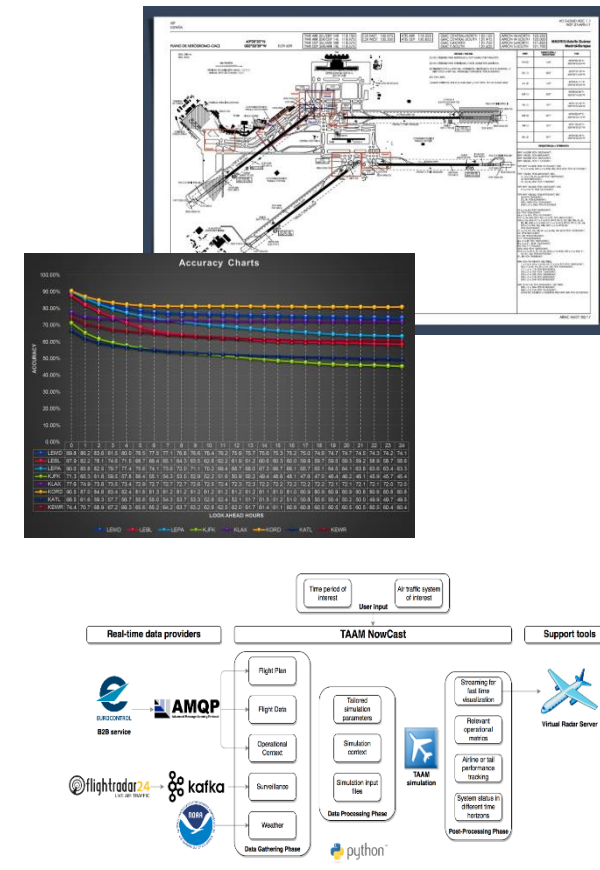
Hidden Markov or Markov decision process

Clustering + Neural Networks/ random forest

Ensemble Meta-Estimators

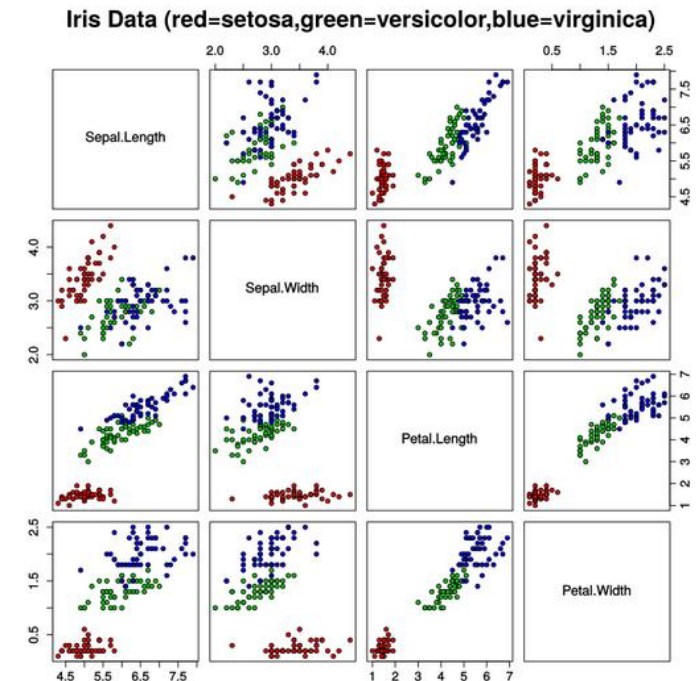
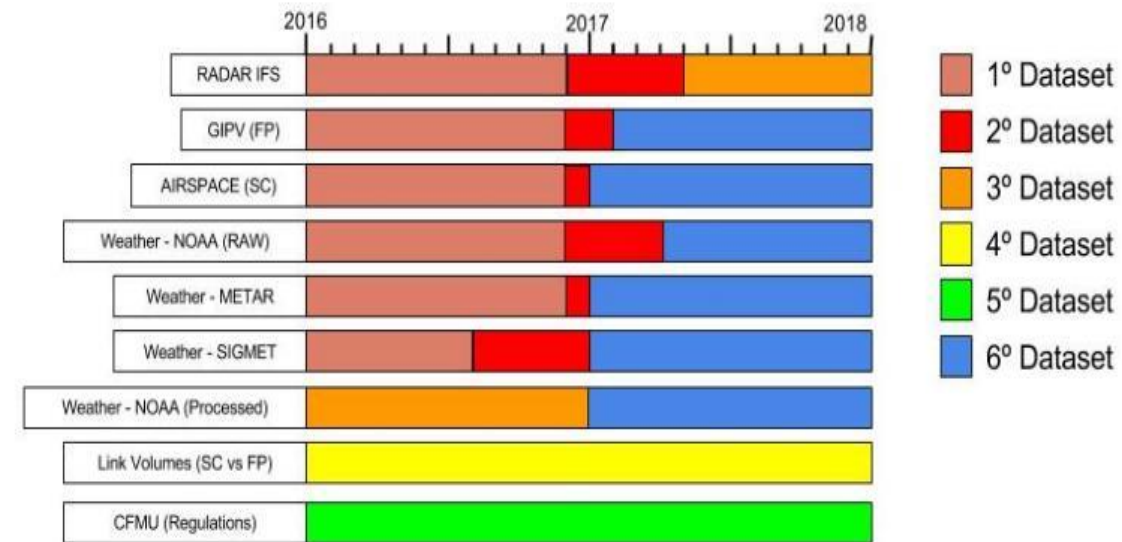
Gradient Boost Machine

- How the complex nature of the ATM system impacts trajectory predictions?
- How can this insight be used to optimize the ATM system?



Challenge 1: Data sources for training

- **Data volumen:** Ex. DART uses two years of data including surveillance, flight plan, airspace, weather
- **Quality of the data:** Noise (frequency, scattering, outliers) and gaps
- **Access to those data sources:** Ex. Partnership with an ANSP
- **Conversion from data to the input of a ML algorithm** (e.g., categorical variables,...)
- **Opportunity:** Common dataset for training and validation (Ex. [Iris flower data set](#) for aviation? Role of Eurocontrol?)



Challenge 2: Algorithms used

- **Variables to be predicted: 4D? 4D+mass?,nD? (Depends on the application, data availability,...)**
- **Temporal sequence of aircraft states**
- **Time between re-trainings (training time and re-training frequency)**
- **Opportunities: Clustering & Time series based algorithms**

| State variable | Symbol | Units |
|---------------------|-----------|------------|
| Latitude | φ | $^{\circ}$ |
| Longitude | λ | $^{\circ}$ |
| Pressure altitude | H_p | ft |
| Elapsed flight time | t | s |
| Aircraft mass | m | kg |



Neural Networks (NN) used to predict the vertical profile of a trajectory [1],

Regression methods used to relate the influences of traffic flow and wind conditions [2]

Dynamically updated clustering methods to infer an estimation of the aircraft intent that represents a flown trajectory [3].

Density-based Spatial Clustering of Application with Noise (DBSCAN) clustering algorithms combined with Interacting Multiple Model (IMM) Kalman filters [4]

K-nearest neighbors in combination of regression methods using wavelet decomposition in Sobolev space [5].

Data-driven Aircraft Trajectory Predictions using Ensemble Meta-Estimators [6]

[1] Le Fablec, Y., & Alliot, J. M. (1999). Using Neural Networks to Predict Aircraft Trajectories. In IC-AI (pp. 524-529).

[2] Kun, W., & Wei, P. (2008, July). A 4-D trajectory prediction model based on radar data. In *Control Conference, 2008. CCC 2008. 27th Chinese* (pp. 591-594). IEEE.

[3] Yang, Y., Zhang, J., & Cai, K. Q. (2015). Terminal-area aircraft intent inference approach based on online trajectory clustering. *The Scientific World Journal*, 2015.

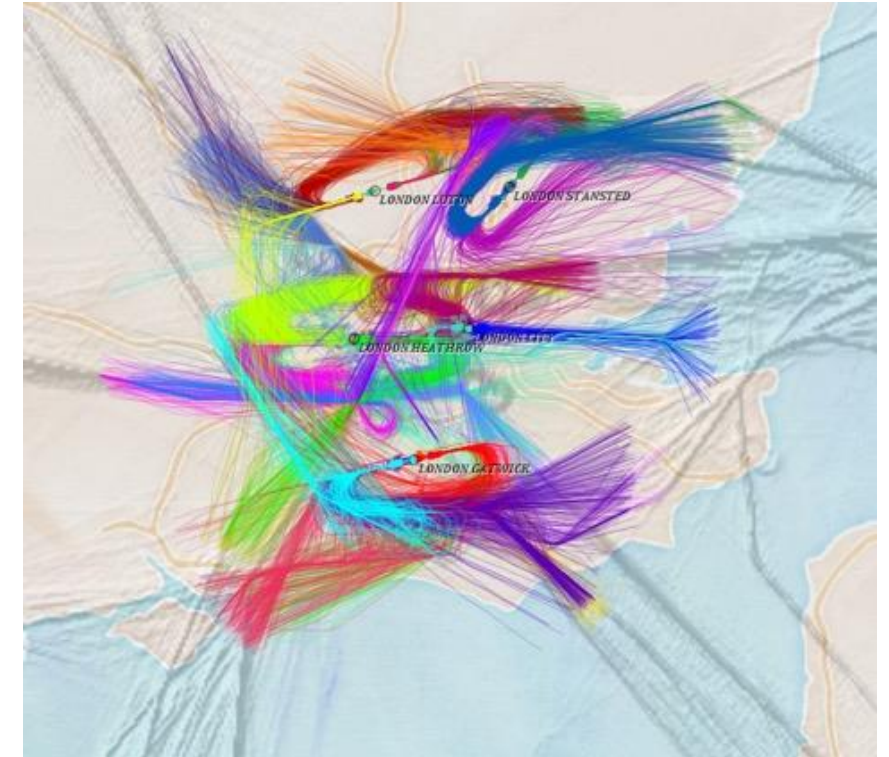
[4] Song, Y., Cheng, P., & Mu, C. (2012, June). An improved trajectory prediction algorithm based on trajectory data mining for air traffic management. In *Information and Automation (ICIA), 2012 International Conference on* (pp. 981-986). IEEE.

[5] Tastambekov, K., Puechmorel, S., Delahaye, D., & Rabut, C. (2014). Aircraft trajectory forecasting using local functional regression in Sobolev space. *Transportation research part C: emerging technologies*, 39, 1-22.

[6] Data-driven Aircraft Trajectory Predictions using Ensemble Meta-Estimators, DASC 2018

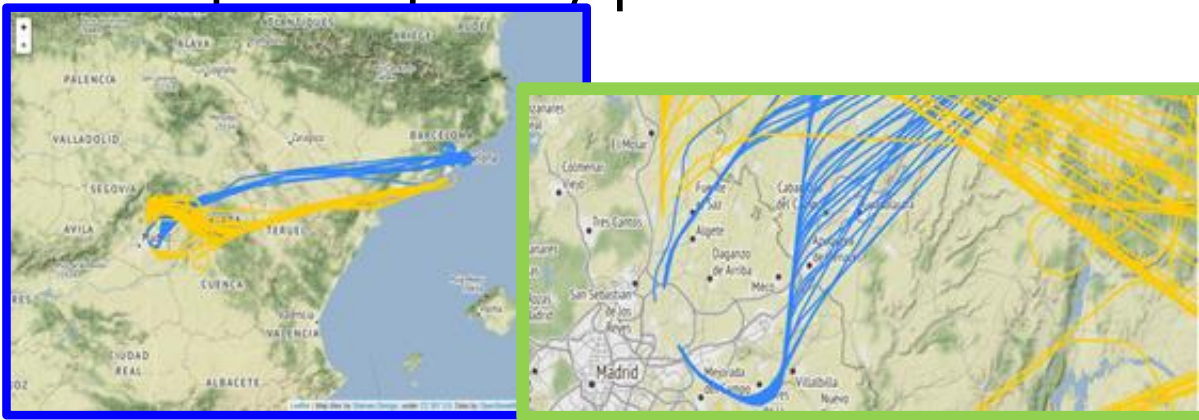
Challenge 3: Data curation

- **Clustering based on O-D or other clusters or no cluster**
 - **Cluster for prediction or cluster combined with another technique**
 - **Normalization of the data**
-
- **Opportunity: Could we with limited data (based on a series of O-D clusters) identify a model so it can be applied to any O-D?**



Challenge 4: “Single” trajectory prediction and “multiple” trajectory prediction

- Single prediction typically based on O-D clusters
- Poor results capturing SIDs/STARs



- Results difficult to assimilate or correlate with model-based

| Latitude | | Longitude | |
|--------------------------|-------------|--------------------------|-----------|
| Feature | Type | Feature | Type |
| Estimated route distance | Numerical | TOC temperature | Numerical |
| Runway arrival | Categorical | Arrival temperature | Numerical |
| TOC temperature | Numerical | Estimated route distance | Numerical |
| Arrival temperature | Numerical | Estimated departure time | Numerical |

- Interaction between clusters for multiple trajectory predictions (traffic)
- Learning from data allows you to learn from de-conflicted data. Advantage or disadvantage?

Challenge 5: Hybrid approach

- **Models obtained from data and used to feed a traditional model-based TP (that only captures a/c dynamic)**
Ex. TP of a Flight plan improved knowing runway and/or SID/STAR assigned
- **a/c dynamic based on data (new data sources, like QAR)**

