Engineering, Test & Technology

Applications of Machine Learning in Aviation

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Airspace Operational Efficiency

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Preceding work with Big Data in BR&T Brazil

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Big Data Management and Processing in the Context of the System Wide Information Management

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***Abstract*—The 4D trajectory management program will require a major shift in infrastructure and operational management processes to deliver accurate and reliable information to trajectory management team. As a result, air traffic management operation will demand Network Enabled Operations (NEO) concepts such as the System Wide Information Management (SWIM) framework to ensure that the decisions are made with the correction information at the right time. SWIM provides standards, infrastructure, and governance practices to allow information exchanging through interoperable services. Consequently, SWIM must provide methods to (a) integrate a large variety of data; (b) filter information in a way that only the relevant ones are retained to explain the results; (c) enable National Airspace System (NAS) operators, pilots, controllers, and traffic flow specialists to extract value of air traffic systems in real-time; and (d) to seek and explore complex and evolving data's relationships. However, SWIM still lacks support to deal with big data analytics and to aggregate computing resources on-demand. As the main contribution of this paper, we describe the challenges and new focuses of SWIM researches. Likewise, we present an architecture to enable big data analytics services in SWIM. The proposed architecture relies on big data processing frameworks to handle data acquisition and data filtering on near-real time taking into account users' objectives; and to guarantee that the data go through all the gives stage of the life cycle of ATM applications, avoiding the silos that may happen in each data analysis stage.**

***Keywords*—System Wide Information Management, Big Data Analytics, Big Data Architecture Management, Air Traffic Management.**

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I. Introduction

Over the last decades, air traffic demand has increased all around the world, and this trend is predicted to continue during the next years. As a result, different programs have started to enhance navigation solutions such as the Single European Sky ATM Research (SESAR) in Europe, the Next Generation Air Transportation System (NextGen) in U.S., the SIRIUS in Brazil, the Collaborative Action for Renovation of Air Transport Systems (CARATS) in Japan, the Future Indian Air Navigation System (FIANS) in India, among others in Canada, China, and Russia. Although these programs address national priorities and particularities, they converge in promoting the evolution of air traffic management (ATM) into an automated, integrated, and collaborative system.

Clearly, the next generation of air traffic management system demands a major shift in infrastructure and in operational management processes to provide accurate, relevant, and reliable information to Air Navigation Service Providers (ANSPs). Likewise, it requires different types of information and Network Enabled Operations (NEO) concepts, such as the *System Wide Information Management (SWIM) framework*, to ensure that the decisions are made with the correct information at the right time [1, 2]. However, many factors must be considered including monitoring capability to help on 4D trajectory approval and surveillance data network (SDN) systems to provide in real-time accurate monitoring data.

SWIM comprises standards, infrastructure, and governance practices to enable the management of ATM information and exchange between qualified parties via interoperable services [2]. Particularly, SWIM aims to address the challenge of implementing a reliable, integrated, and interoperable air-ground communication

Outline

- **Introduction**
  - Motivation
  - Challenges
- **Background**
- **Research areas**
  - Robustness
  - Deep sense learning
  - Recent examples
- **Summary**

Machine Learning (ML) is defined by widely accepted definitions as:

“A computer program is said to learn from experience with respect to some class of tasks and performance measure if its performance at those tasks improves with experience.”

— Tom Mitchell

or:

“Field of study that gives computers the ability to learn without being explicitly programmed.”

— Arthur Samuel, ca. 1959

Supervised & Unsupervised Learning Both Provide–

System Performance Enhancements

Fewer Errors

Better Efficiency

Increasing Accuracy

Yielding

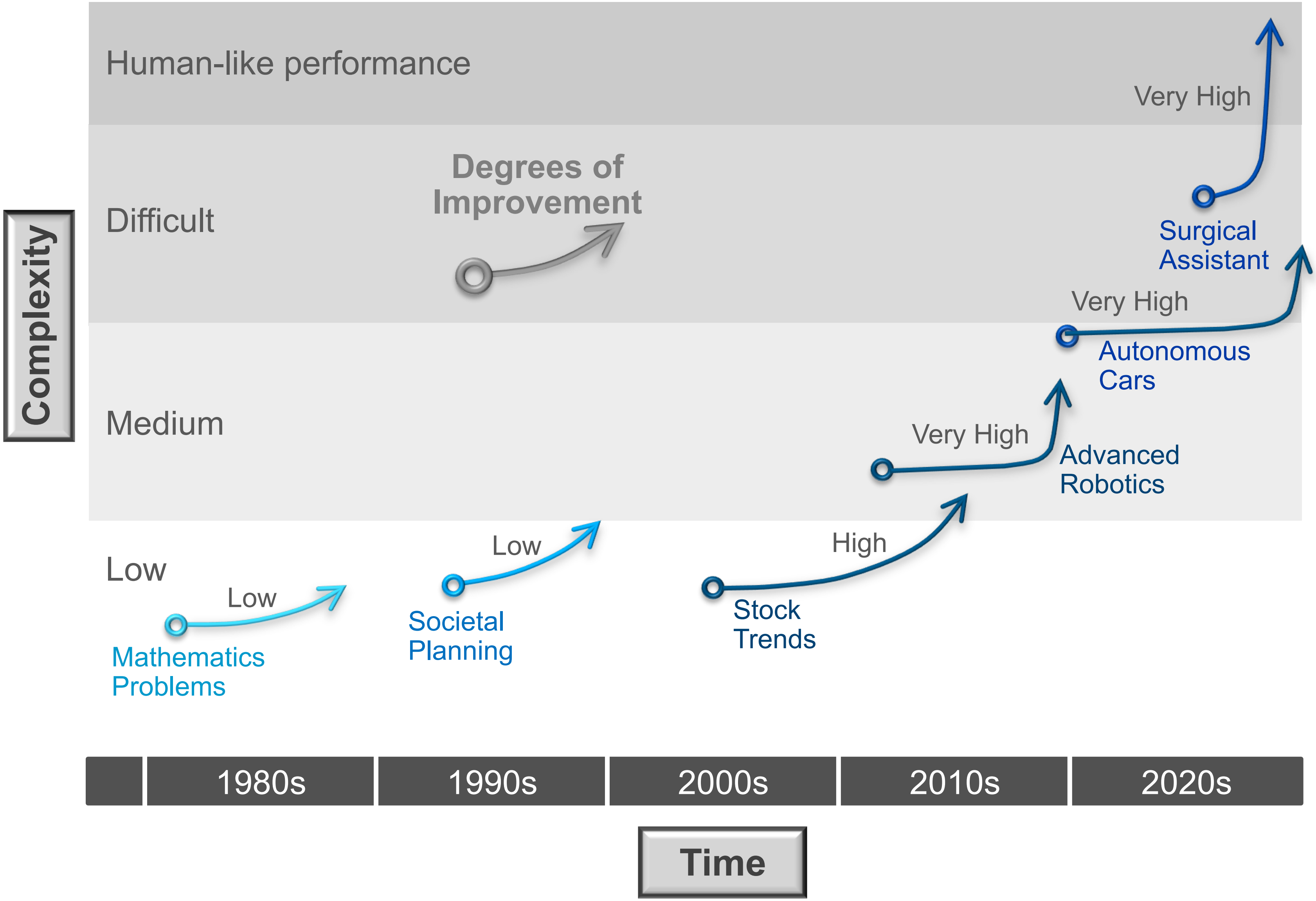
Smarter Devices

Challenges for Machine Learning in Aviation

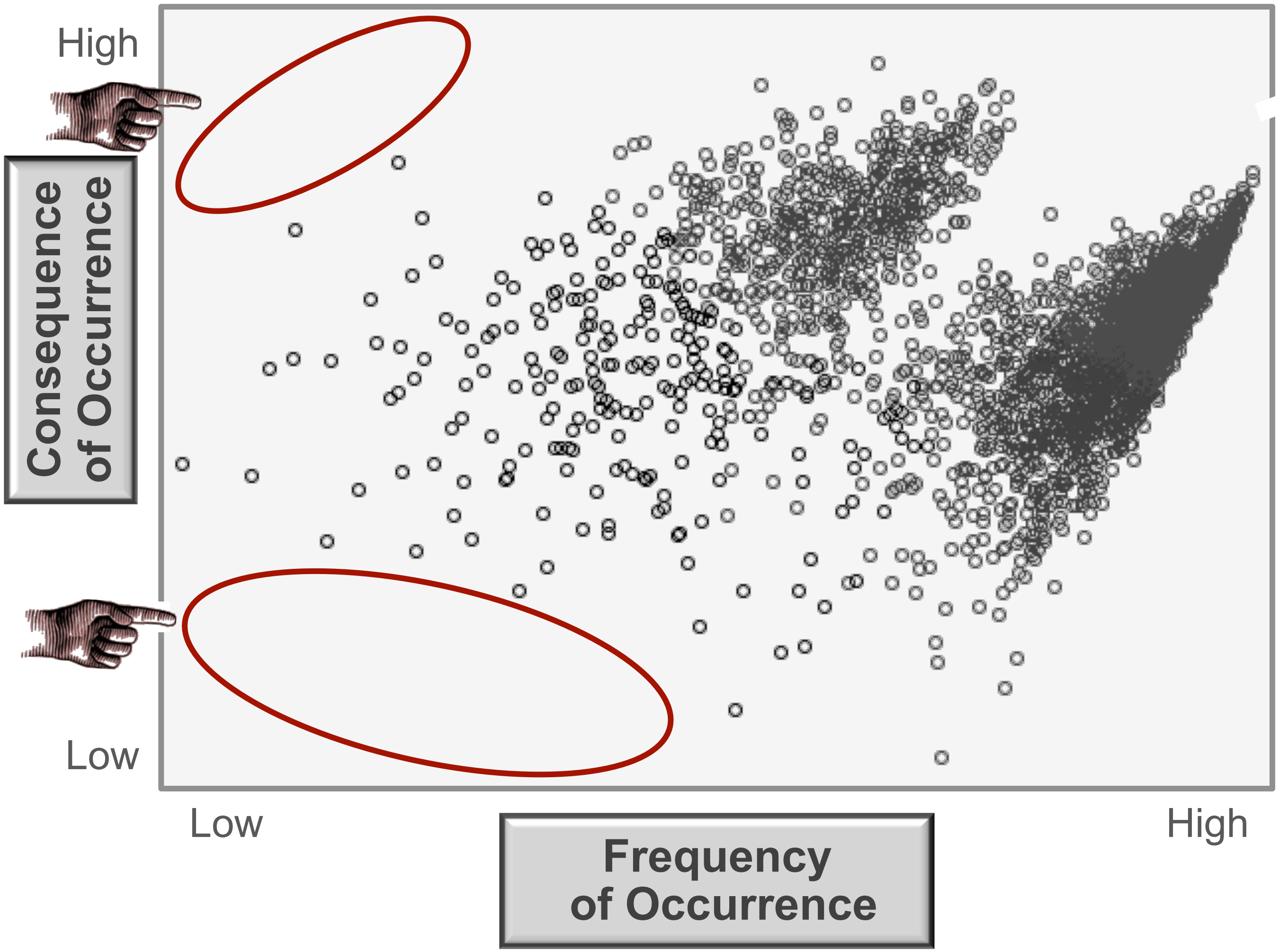
- **Non-stationary stochastic processes**
- **Anomaly detection**
- **Learning in on-line settings**
- **Others include:**
  - Real-time operation
  - Competing systems

A Sample of Machine Learning Applications Profile

50 Years of History



Importantly, ML Cannot Ignore Training at the Corners but… Methods Do Not Extrapolate



High-Stakes Applications Require **Robust AI**

In aviation, best practice for AI / ML robustness must guarantee safety, even with the presence of:

- **Incomplete models**
- **Unmodeled phenomena**

Why is **Unmodeled Phenomena** a hard fundamental problem?

1) It is impossible to model everything

- **Qualification Problem:**
  - It is impossible to enumerate all of the preconditions for an action
- **Ramification Problem:**
  - It is impossible to enumerate all of the implicit consequences of an action

2) It is important *NOT* to model everything

- **Fundamental theorem of machine learning**

$$\text{error rate} \propto \text{model complexity} / \text{sample size}$$

- **Corollary:**
  - If sample size is small, the model should be simple
  - We must deliberately oversimplify our models!

Deep Sense Learning (DSL)

Objective

- Need for robust scene understanding in **cluttered** environments and data analytics with **few labeled** data
- Our objective is to dramatically reduce false alarms for autonomous recognition and learn with 1000x less labeled data

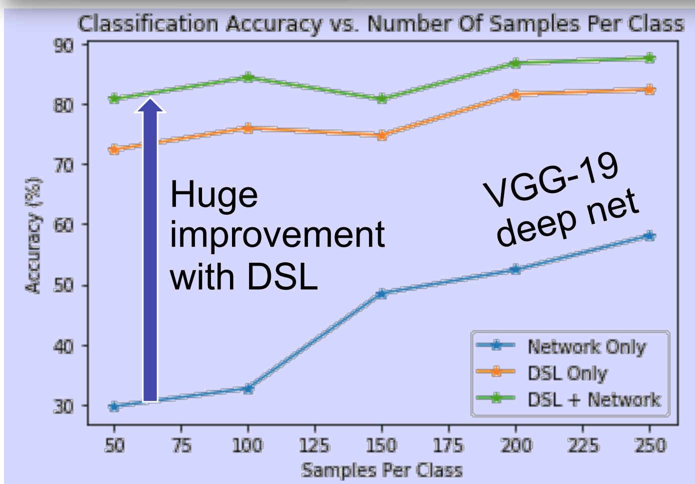
Benefits

Autonomous navigation

Novelty detection

Target recognition

Performance



- For 50 labeled samples per class, DSL reduced errors from 70% for deep learning to only 18%

Explainable Machine Learning

Deep Sense Learning technology explains the inner workings of complex machine learning models

Challenge

High-performance ML models are black boxes

Innovation

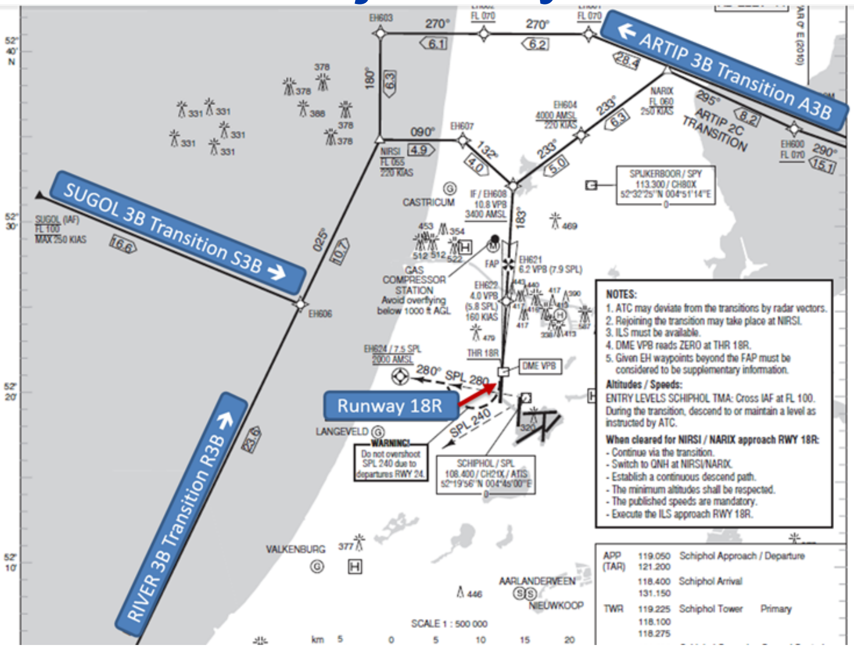
Explainable Traces (X-trace) provide fine-grained view of ML decisions

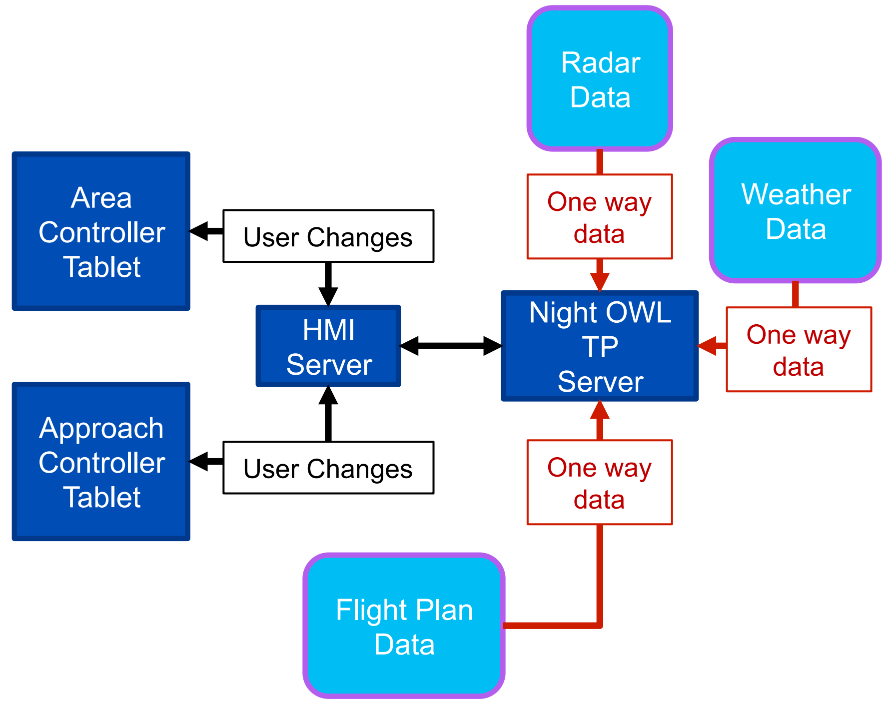
Approach

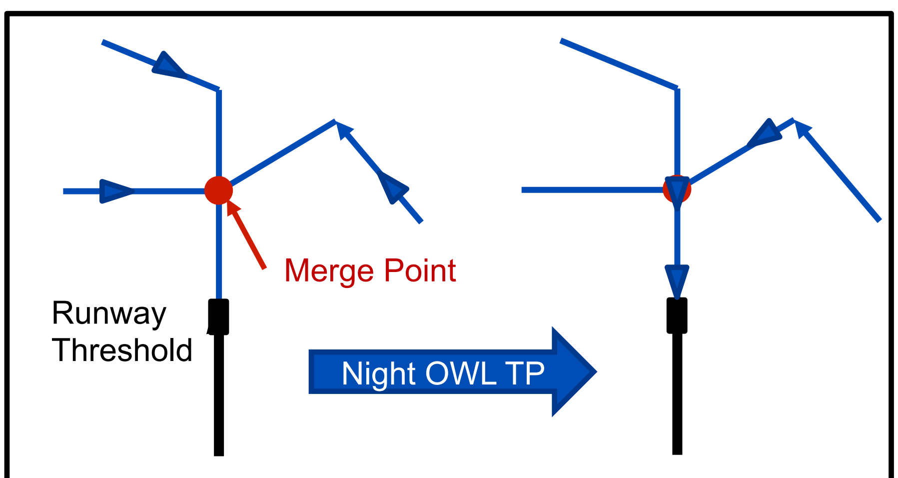
Decompose input into hierarchy of decision-relevant attributes

DSL explains machine learning mistakes and how to correct them

Aircraft Trajectory Prediction Using Advanced Analytics







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Summary

- **The AI/ML science in is rapidly evolving**
- **The scientific evolution goes in parallel to the evolution of autonomous transportation systems**
- **Robustness is essential, or ML will produce unexpected outcomes**