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ASSEMBLY — 41ST SESSION

TECHNICAL COMMISSION

Agenda Item 33: Other issues to be considered by the Technical Commission

PREDICTIVE ANALYTICS FOR TRAFFIC FLOW MANAGEMENT

(Presented by the United States)

EXECUTIVE SUMMARY

This paper discusses the potential opportunities for developing and deploying machine learning (ML) models to support the execution of traffic flow management (TFM) activities in the civil aviation context. Benefits and challenges are highlighted, along with the need to follow best practices in machine learning operations (MLOps) when administering the ML lifecycle. Early prototype ML models for predicting surface congestion and multi-airport delay in the United States (U.S.) National Airspace System (NAS) serve as examples.

Strategic Objectives:	This information paper relates to the Strategic Objective of Safety and Air Navigation Capacity and Efficiency
Financial implications:	Not applicable
References:	

1. INTRODUCTION

1.1 Data is ubiquitous in the civil aviation domain, and ML models can leverage this data to improve decision making, and thereby safety and efficiency.

1.2 In comparison to classical statistical analysis techniques, ML models can provide deep and powerful insights into aviation data relationships that go beyond current understanding.

1.3 These insights can inform new perspectives and promote new and improved operational planning and response. Notably, data-driven ML models can help mitigate some of the issues that complicate human decision making, such as personal biases and short-term memory.

1.4 In the context of TFM, ML models can provide decision support in both strategic and tactical environments. Strategically, an ML based model for predicting and recognizing traffic flow patterns could inform the right initiatives to resolve constraints, and a delay prediction model could inform downstream scheduling to help mitigate airspace congestion hours in advance. Tactically, a surface congestion prediction model could alert Traffic Management Coordinators when ground traffic on the "apron" is approaching capacity, thereby promoting active resolution before the situation worsens.

1.5 The MITRE Corporation, in support of the U.S. Federal Aviation Administration (FAA), has developed prototype models for both multi-airport delay prediction and surface congestion prediction. While still under development, the FAA's early feedback suggests that these models will have decision support operational value.

1.6 Beyond predicting future events, ML models can also be trained to categorize historical events to improve human understanding of past successes and failures (i.e., post-operational analysis), and even recommend specific actions to mitigate congestion and other undesirable outcomes.

2. CRITICAL IMPORTANCE OF MACHINE LEARNINGOPERATIONS (MLOPS)

2.1 ML models are dynamic in that they must evolve over time to be effective. Their success is based, in part, on how well the underlying data used to train the model (predictive or otherwise) is consistent with current operations. As such, ML models must be updated frequently to stay relevant.

2.2 The practice and process of iteratively re-training and re-deploying ML models in a systematic and repeatable way is commonly known as machine learning operations (MLOps). See Figure 1 for an illustration. There is consensus among the ML community that the adoption of MLOps best-practices is essential to the proper execution of ML model lifecycles. ML models are simply not sustainable unless organizations invest in the adoption of MLOps.

2.3 The importance of MLOps and model sustainability will be further amplified as "learning automation" continues to play a larger role in civil aviation in the coming decades – in particular, as automated systems become interdependent. In this future, the failure of one piece of automation could negatively impact the entire system.

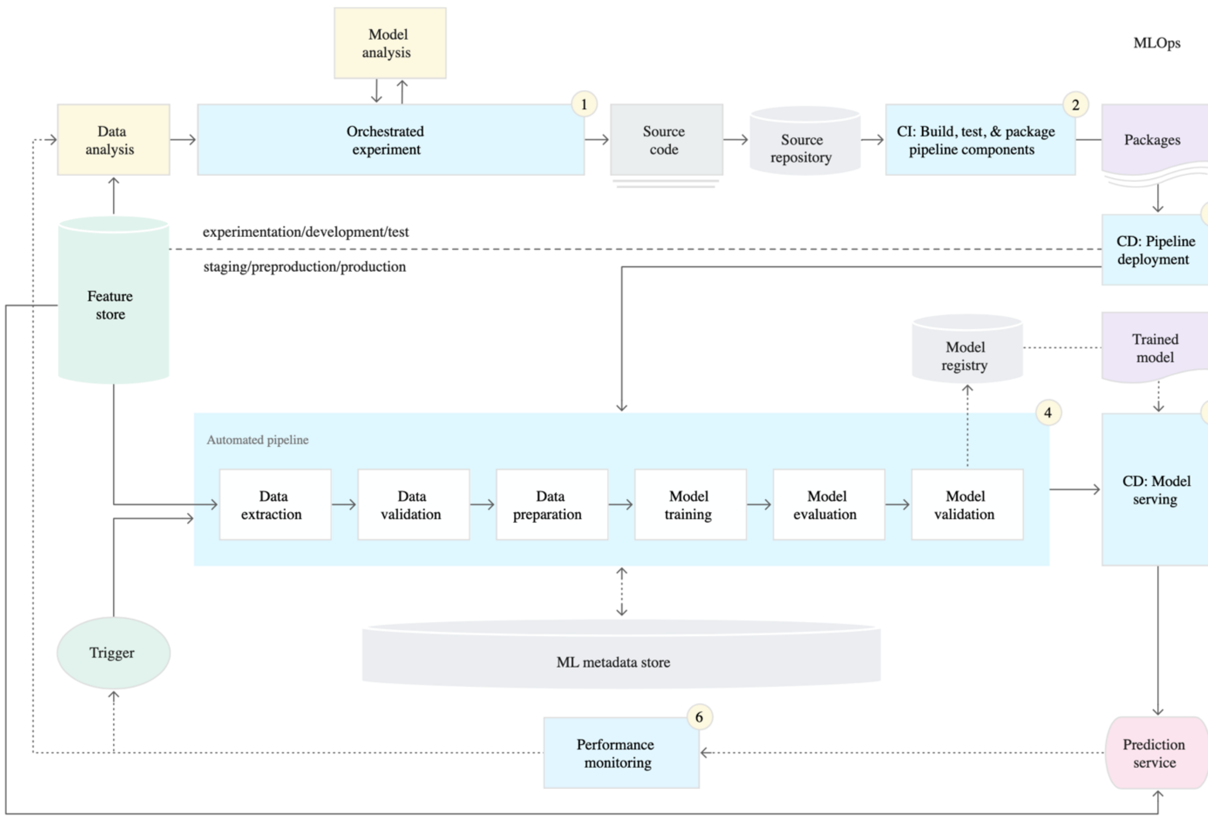

Figure 1. Illustration of a mature, automated MLOps pipeline. Taken from *https://cloud.google.com/architecture/mlops-continuous-delivery-and-automation-pipelines-in-machine-learning*

3. INVESTMENT NEEDS AND OTHER CHALLENGES

3.1 Considerable investment is required for an organization to properly execute MLOps over the lifetime of one or more ML based capabilities. Areas of investment include (i) computational infrastructure, (ii) software tooling, (iii) ML expertise (i.e., knowledge and people), and (iv) governance.

3.2 MLOps generally requires on-demand access to both CPUs (central processing units) and GPUs (graphics processing units), for data processing and model training, respectively. While cloud computing companies such as Amazon Web Services simplify cloud adoption by offering infrastructure as a service (IaaS), it is still incumbent on the organization to adapt its data governance and stewardship practices to the cloud environment, which may be a non-trivial process. Furthermore, estimation of cloud computing costs for budgeting purposes would require forethought regarding the scale and frequency at which MLOps will be executed.

3.3 Streamlining development and deployment is key to MLOps success. ML-focused organizations gravitate towards “containerization”, by which the individual tasks of the MLOps pipeline are delegated to separate containers that are pre-configured with appropriate software and library dependencies. Containerization further magnifies the value of IaaS solutions since containerized architectures can be deployed to new cloud environments with minimal changes. This simplifies ML transition activities, e.g., between organizations. To leverage containerization, however, organizations must first scope out the interconnected components of the MLOps pipeline and have a clear long-term plan for execution. Software engineering expertise is required to ensure that containers are built to specification.

3.4 More generally, an interdisciplinary staff with background that includes software engineering, data science, and ML is required to successfully execute the MLOps lifecycle over time. Responsibilities include setup and maintenance of the compute environment, establishing connections for data ingest and ensuring data integrity over time, and monitoring model performance as real-world operations evolve. ML expertise is needed to diagnose and resolve issues related to model performance – for example, understanding why a model is underperforming in the field, and improving performance through model re-train, changes to data processing, or other means.

3.5 The MLOps lifecycle must be an iterative process whereby stakeholders in the civil aviation arena (e.g., air traffic controller, traffic flow managers, and flight operators) who are leveraging ML based technologies can provide critical feedback to improve subsequent iterations of ML models. Such a feedback loop requires open channels of engagement between stakeholders and model developers and infrastructure designed to elicit and collect feedback in a digital form (e.g., via a user interface to software). Adoption of "explainable" ML models – whose predictions and recommendations can be traced back to human-interpretable data – may also be needed to gain stakeholder trust.

3.6 Organizations practicing MLOps must develop new best-practices in governance to ensure that the process conforms to ethical and legal principles. Governance as it relates to data sharing and security is also critical due to the central role of data in ML.

3.7 While daunting, the challenges of adopting MLOps can be overcome in the civil aviation context. For example, the previously mentioned surface congestion prediction and multi-airport delay prediction models – under development at The MITRE Corporation – have followed the MLOps paradigm with some success. Most notably, by following the MLOps practice of continuous development, the ML team has been able to engage the FAA sponsor more effectively, elicit feedback, and quickly iterate on model enhancements that increase each capability's operational suitability.

4. **CONCLUSION**

4.1 ML can be transformative in the civil aviation context, deriving insights from a wealth of data to improve safety and efficiency.

4.2 However, successful execution of ML requires an up-front investment in MLOps. MLOps is a non-trivial undertaking that poses numerous challenges in staffing, education, software and technology, and various governance issues.

4.3 The Assembly is invited to note the information provided in this paper.

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