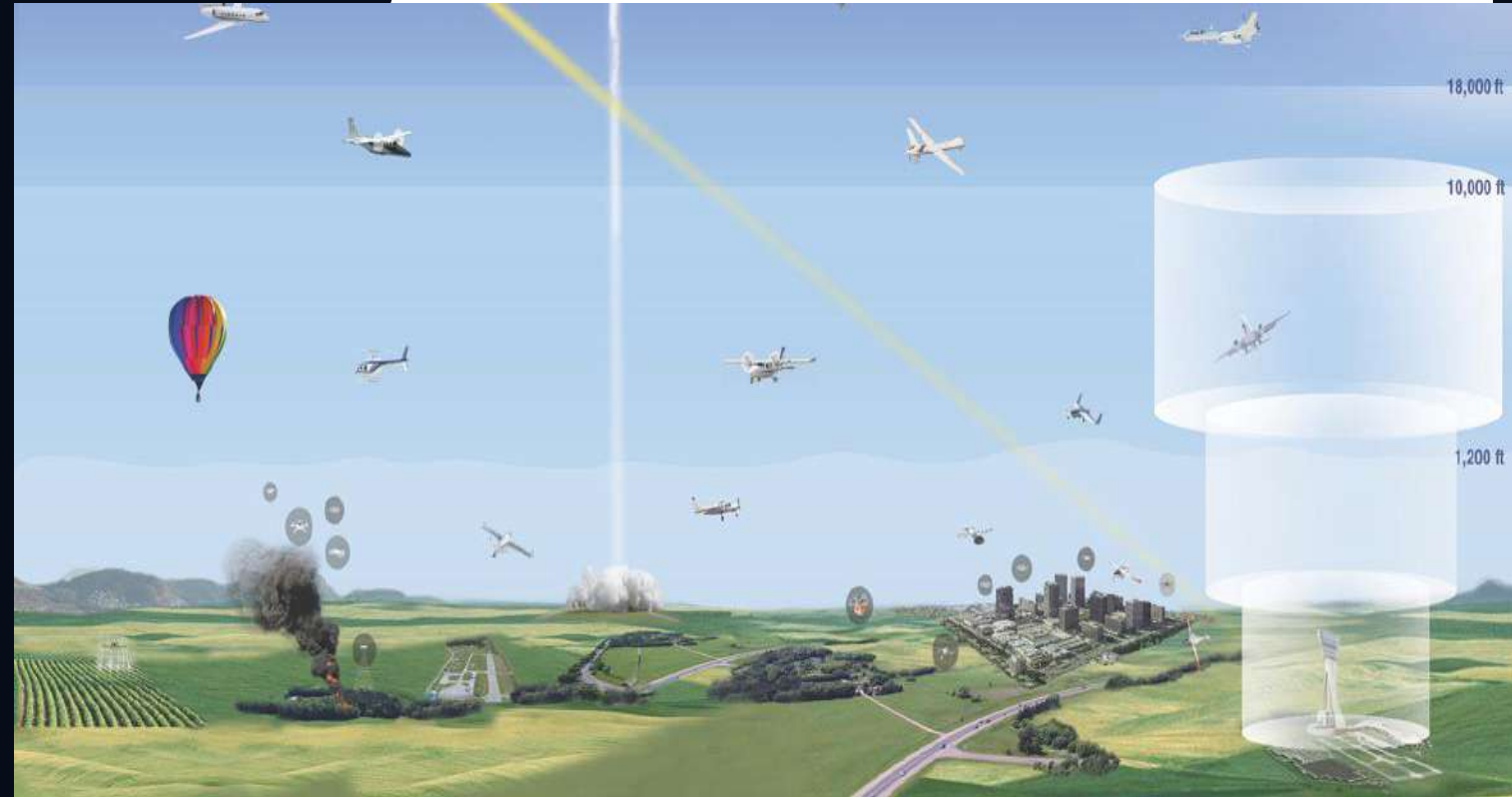




Responsible AI Framework for Air Traffic Management



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OUTLINE

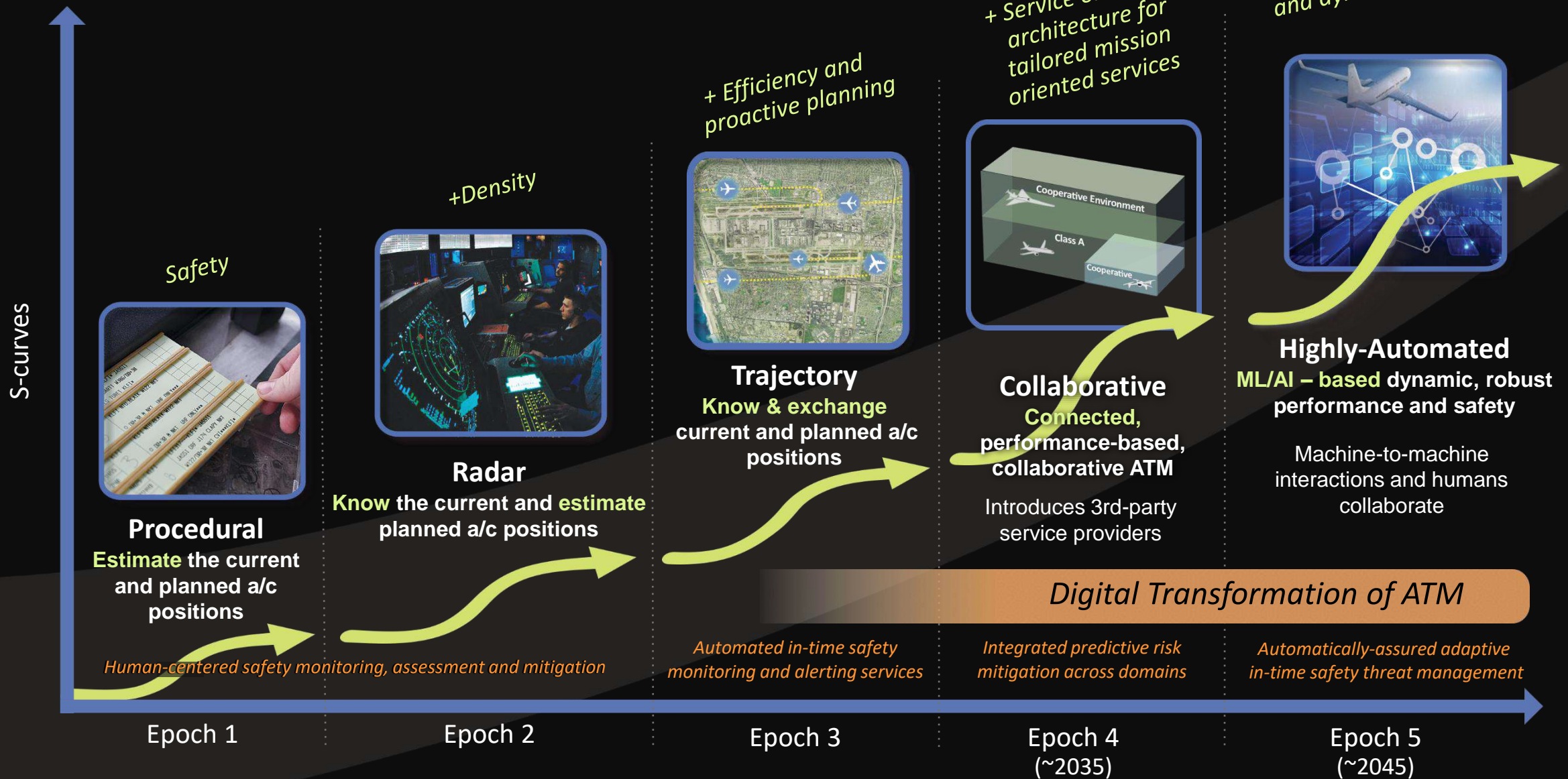
- Evolution Airspace Operations Future
- Key Proposal
- Responsible AI Framework
- Use Cases
- Collaboration and Harmonization



Hypothesis: Role of Automation

- Future system will require increased levels of automation to address increased diversity, density, environmental considerations resulting in higher complexity
- Historical basis for this hypothesis

Evolution of Airspace Operations and Safety



Transition to UTM-inspired Airspace Traffic Management



Current ATM



All services are provided by FAA

Human address off-nominal situations and contingencies to ensure safety

Very little interaction among users and third parties

- Human at the epi-center of information integration
- Every data for every vehicle moves through FAA systems
- Management by clearances
- Each change is focused on domain-specific FAA system



UTM-inspired-ATM



Services are provided FAA and third-parties

Automation addressed off-nominal situations and contingencies to ensure scalability while maintaining safety

Users collaborate/cooperate for efficiency, preferences for flights into constraints resources

- Automation at the epi-center of information integration
- New paradigm: Digital, connected ecosystems, outside applications
- Movement towards management by exceptions
- Each change is focused on trajectory optimization

Research Needed: Architecture, data exchanges, service allocation/roles/responsibilities, rules of engagement, performance requirements for aircraft and airspace system technologies, automation for contingency management and disruption handling, machine learning environment and algorithms for continuous improvement, safety assurance/certification/acceptance approaches, and technology transfers.

Key Question

- Will automation be able to manage off-nominal, non-normal, unexpected, contingency situations?

Proposal

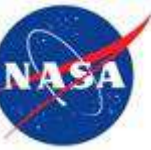
- Type 1: Decisions that are reversible, strategic, or impact only efficiency, capacity, sustainability but do NOT impact safety of operation directly
- Type 2: Decisions that are irreversible, tactical, and COULD impact safety of operation directly including other measures of performance



Responsible AI Framework: Factors

Particularly for Type 2 Decisions

- Explainability
- Transparency
- Visibility in Learning – external validation before implementation
- Security
- Safety
- Trustworthiness
- **Stay within the rules of behavior**



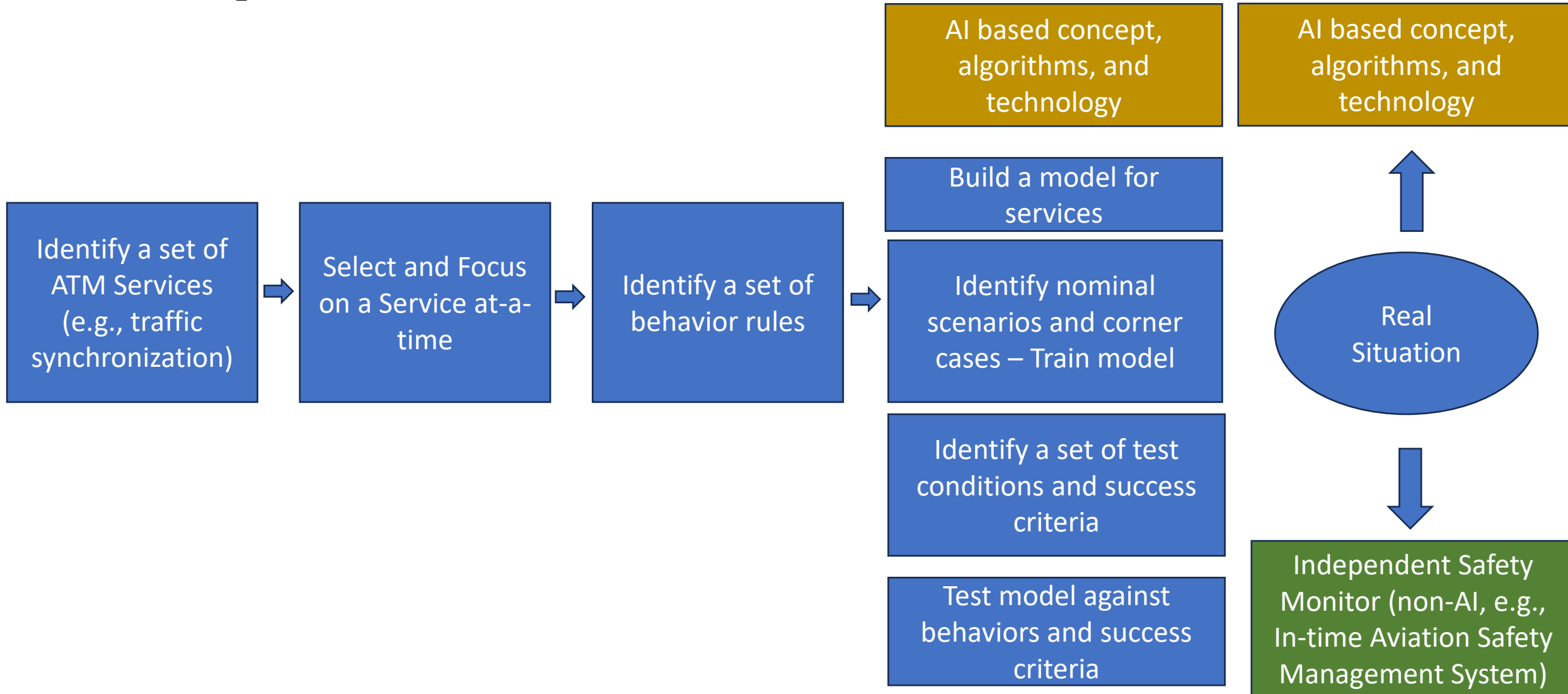
Behavior Rules

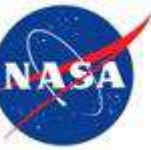
- Every system or subsystem must have clear “system behavior” rules to ensure compatibility and harmonization with rest of the universe
- Example, Asimov’s Rules
 - First law is that a robot shall not harm a human, or by inaction allow a human to come to harm.
 - Second law is that a robot shall obey any instruction given to it by a human, and
 - Third law is that a robot shall avoid actions or situations that could cause it to come to harm itself.
- Challenge with Asimov’s rules were not easily testable

Example Behavior Rules

- Flow management System
 - Demand should not exceed capacity in any given time
- Conflict management system
 - No two aircraft should ever come closer than minimum separation
- Surface management system
 - Two aircraft should not occupy the same runway at the same time

Responsible AI Framework: A Process





Safety Monitor - Proposal

- Not human
- Layer of deterministic automation
- Not intended to duplicate same capabilities such as AI-based approaches for total system performance
- Safety monitor – manages for safety! One function.
 - Like humans do today – safe, expeditious, and orderly flow in that sequence
 - We have precedence – Traffic Collision Avoidance System (TCAS)
- Architecting a new system is key
- System-level “digital twin” running in the background

Use Cases

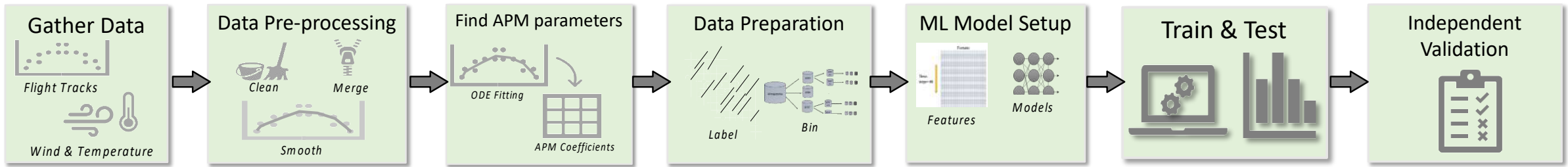
ML based trajectory prediction

Goal: Improve ETA predictions by providing accurate ML derived aircraft performance model (APM) parameters

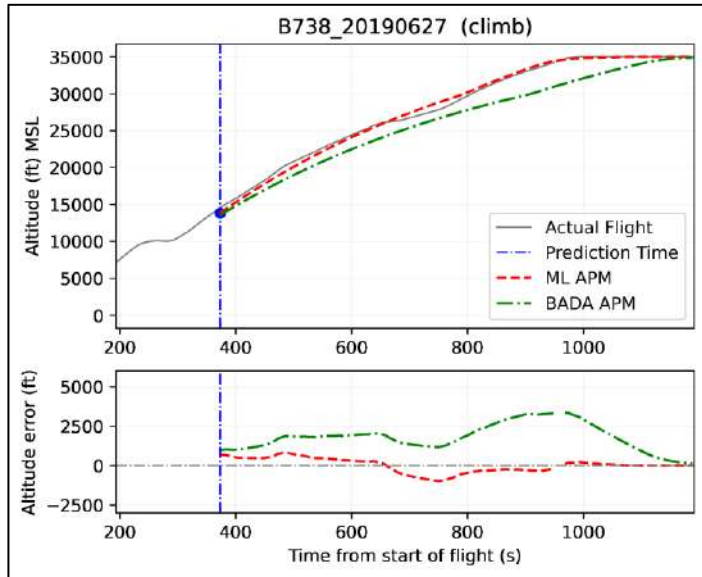
Challenges: Highly coupled parameters, proprietary values, no ground truth (labels) available.

Approach:

- Collected and processed data from **thousands of historical flights**
- Used physics-based approach (ODE-fitting) to obtain best APM coefficients for each flight
- **Trained ML model** to capture relationship between characteristics of flights and ‘best’ APM coefficients



Example result



ML-based method shows significant improvement in trajectory prediction compared to traditional model parameters

Runway Configuration Assistance (RCA)

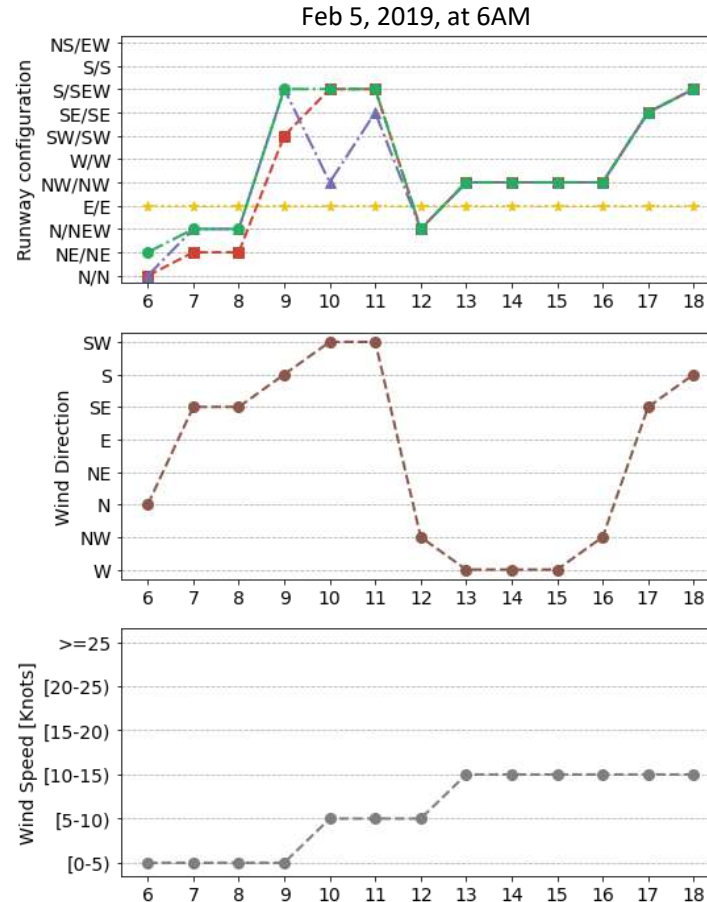
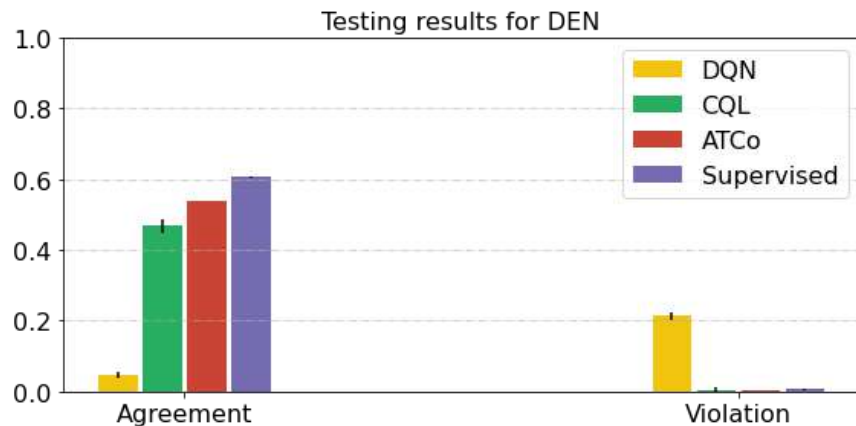
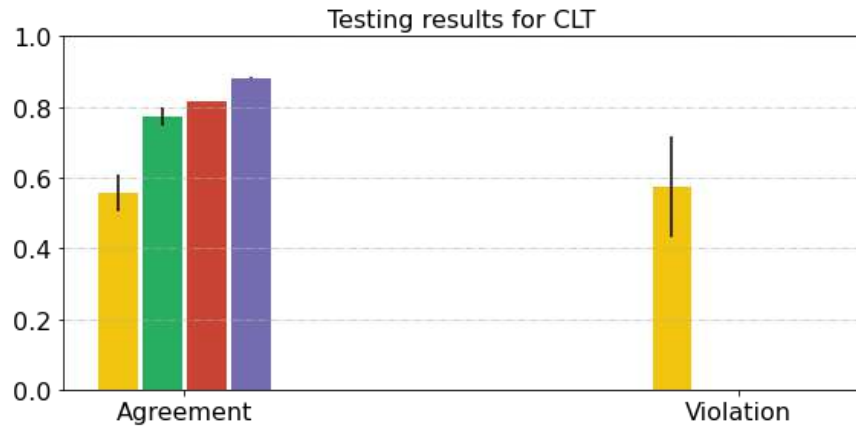
Goal: Create an AI/ML tool to predict/recommend optimum time frame for runway configuration changes based on historical data and weather/traffic forecasts, *without access to simulators*

Validation metrics:

- Agreement with historical decisions
- Violation of obvious configuration scenarios

Approach:

- Processed traffic and weather data from FAA's ASPM, NASA's Sherlock and NOAA's LAMP
- Developed supervised learning to mimic the controllers (ATCo)
- Developed offline model-free reinforcement learning (CQL) to enhance decision-making of the ATCo



RCA tool and supervised learning show significant performance in CLT and especially in DEN, despite its complexity of runway configurations

Visualization dashboard:

- Prediction of the configuration changes given the scheduled traffic and forecast of weather conditions.
- Can be used by ATCo to identify optimum time-interval for configuration changes.



ATCSCC Webinar transcription

Goal: Utilize recent trends in AI/ML to provide automated transcriptions of ATCSCC webinar audio and extract relevant information from the transcript to help specialists.

Challenges: Unstructured audio data, highly domain-specific. Creating manual transcriptions takes time.



ML Models:

- **Speaker Diarization:** Split speaker segments from long audio
- **Speech2Text:** Convert audio into text transcriptions.
- **Audio-Lexical Inverse Text Normalization:** Add text formatting, punctuation, and capitalization to raw text.
- **Named Entity Recognition:** Used to extract key words and phrases from text transcriptions.



Transcription

currently on the OIS we have to boston newark laguardia and seattle ground delay programs in place

Text Formatting (ITN)

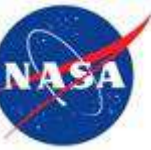
Currently **on the OIS** we have **to** Boston. Newark, LaGuardia and Seattle **GDPs** in place.

Microsoft Baseline

Currently **only OS** we have **the** Boston, Newark, LaGuardia, and Seattle **Ground lay programs** in place.

Analytics

Currently on the OIS we have to **Boston AERODROME** . **Newark AERODROME** , **Laguardia AERODROME** and **Seattle ARTCC** GDPs in place.



Collaboration and Harmonization

- Factors for Responsible AI
- Behavioral rules for ATM enterprise
- Basic architecture – safety monitor construct
- AI-based technology will be secret sauce but set of test conditions and success criteria does not have to be



Embracing Innovation in Aviation while Respecting its Safety Tradition

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