Responsible AI Framework for Air Traffic Management

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OUTLINE

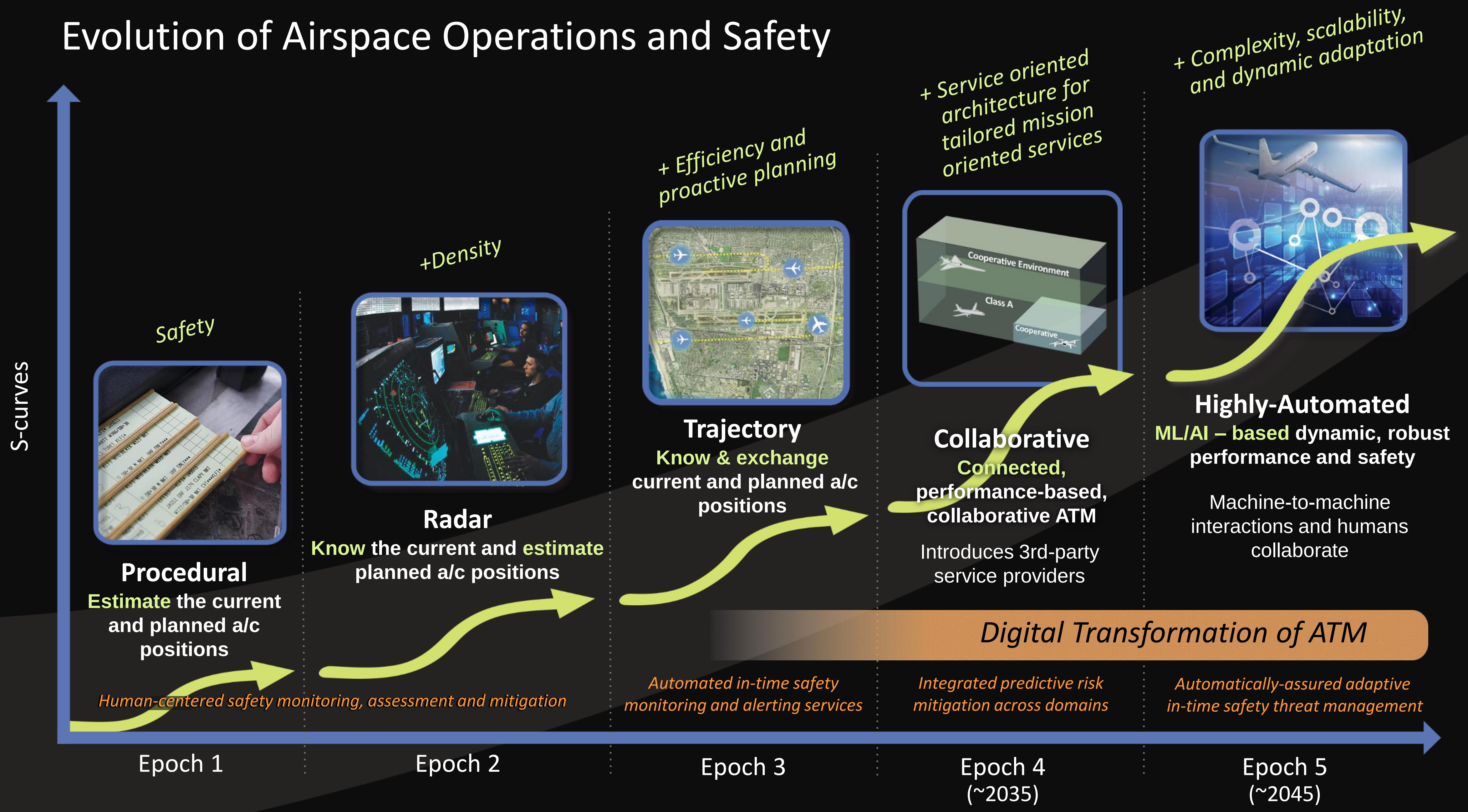
- Evolution Airspace Operations Future
- Key Proposal
- Responsible AI Framework
- Use Cases
- Collaboration and Harmonization

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	UTM-inspired-ATM
All services are provided by FAA	Services are provided FAA and third-parties
Human address off-nominal situations and contingencies to ensure safety	Automation addressed off-nominal situations and contingencies to ensure scalability while maintaining safety
Very little interaction among users and third parties	Users collaborate/cooperate for efficiency, preferences for flights into constraints resources
• 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	• 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

Identify a set of ATM Services (e.g., traffic synchronization)

Select and Focus on a Service at-a-time

Identify a set of behavior rules

AI based concept, algorithms, and technology

Build a model for services

Identify nominal scenarios and corner cases – Train model

Identify a set of test conditions and success criteria

Test model against behaviors and success criteria

AI based concept, algorithms, and technology

Real Situation

Independent Safety Monitor (non-AI, e.g., In-time Aviation Safety Management System)

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

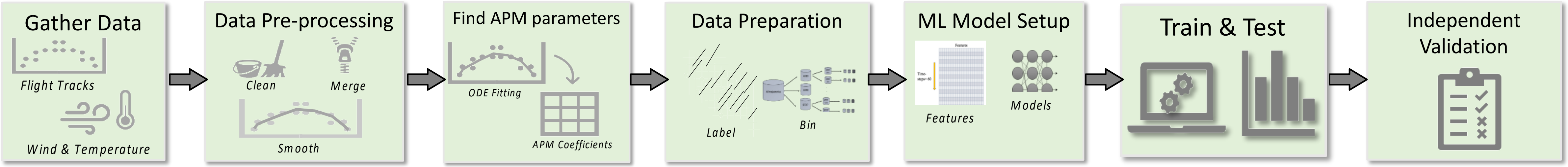
ML based trajectory prediction

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

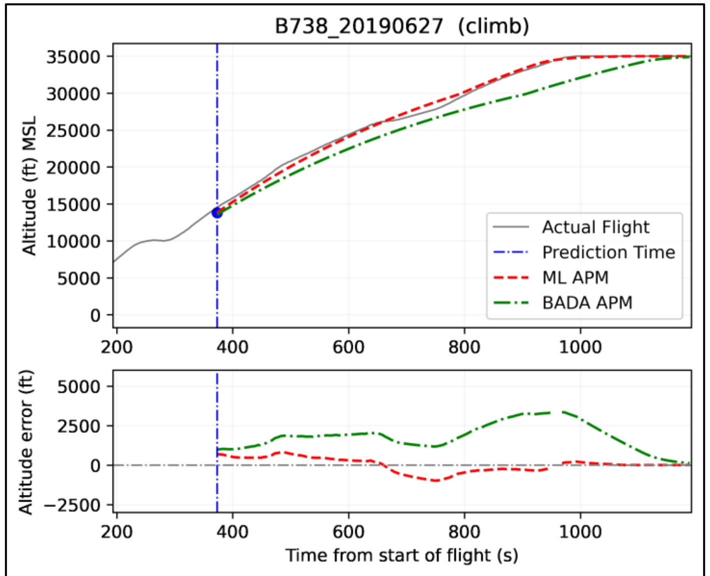
Challenges: Highly coupled parameters, proprietary values, no ground truth (labels) available.

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



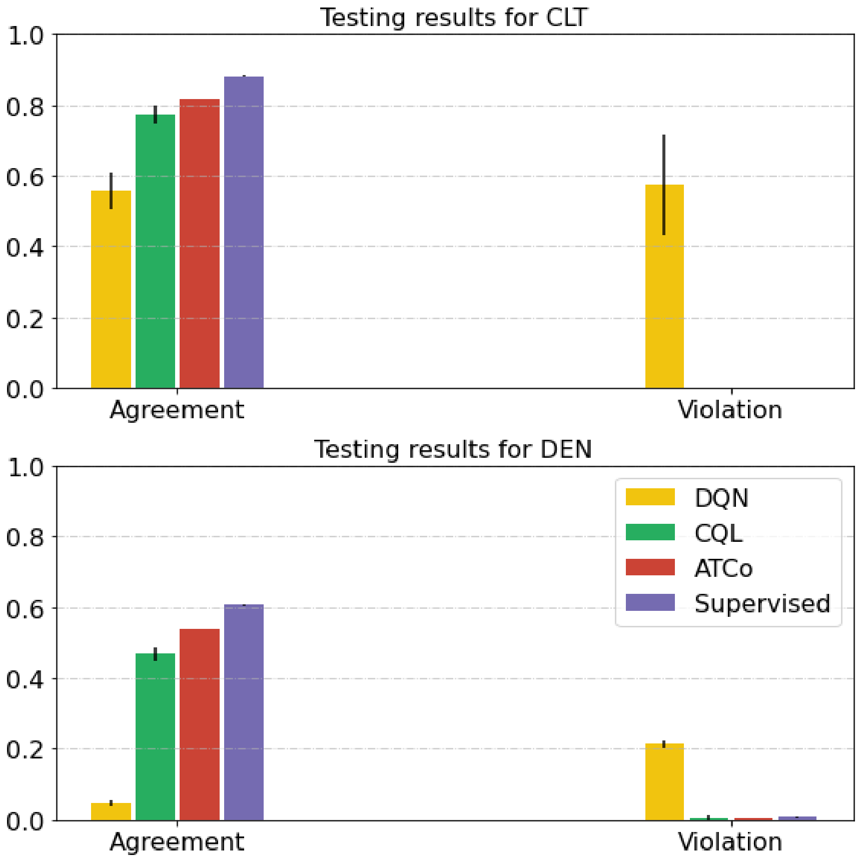
ML-based method shows significant improvement in trajectory prediction compared to traditional model parameters

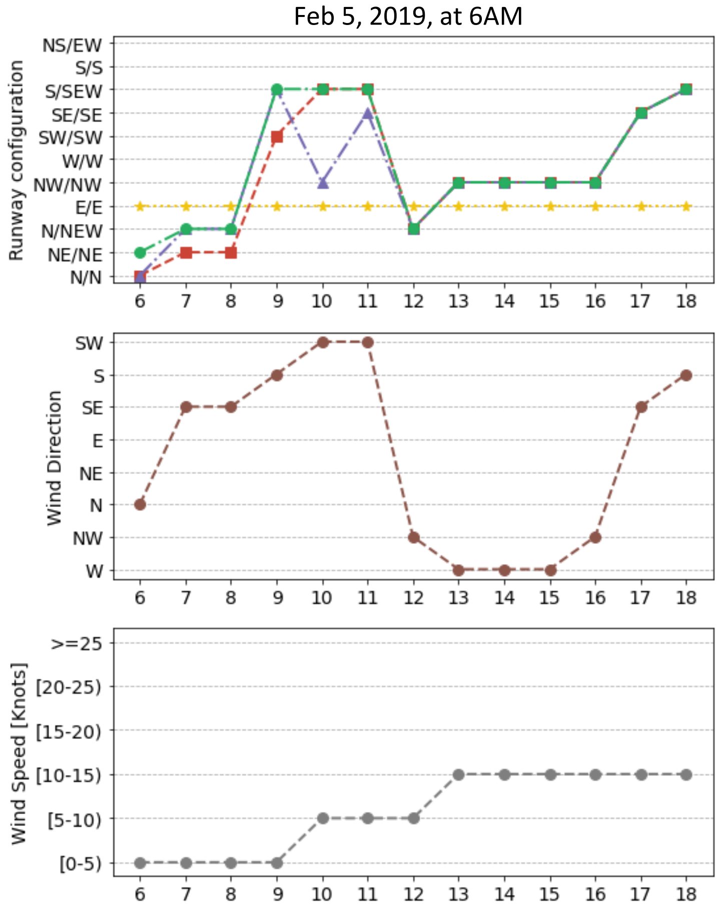
Runway Configuration Assistance (RCA)

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.

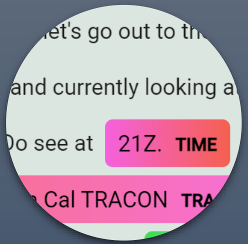
ATCSCC Webinar transcription

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.

ATCSCC Webinar Speech2Text

- Collect and preprocess
- Automatically create text-based transcriptions



Digital Information

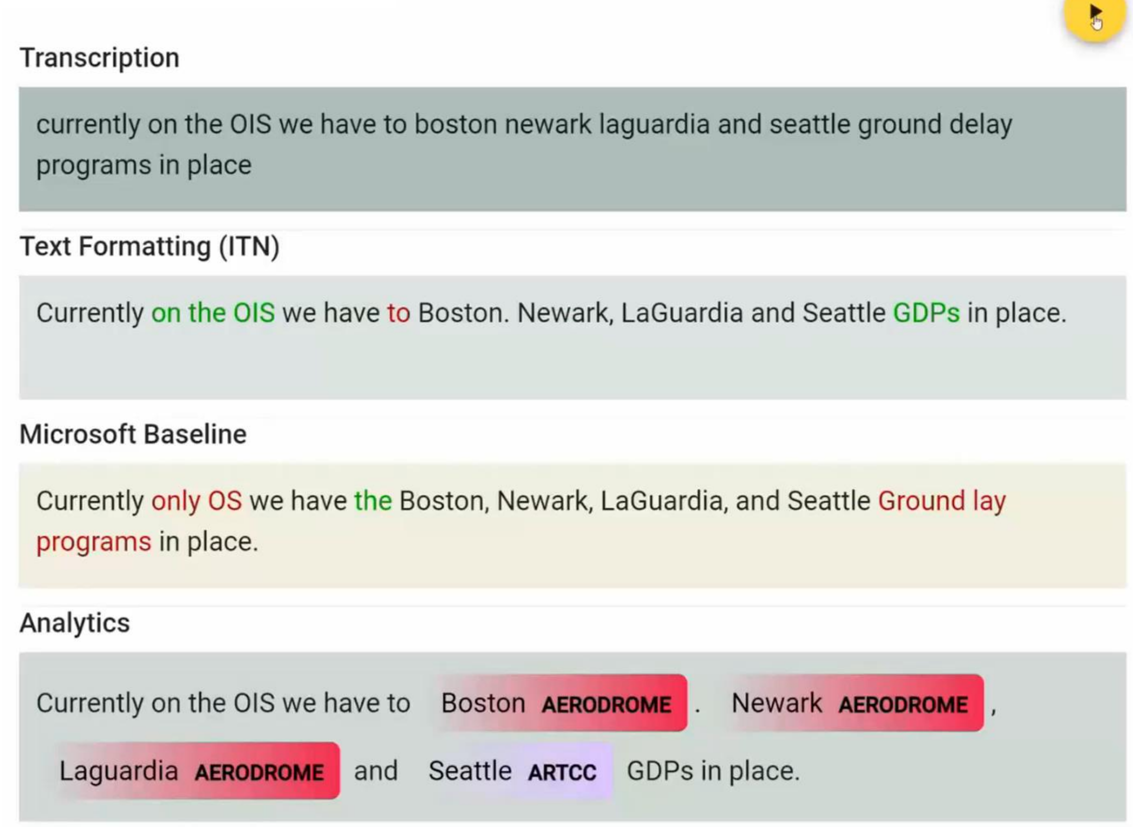
- Provide downstream information extraction and text processing
- Digital TMIs

Outcomes

- More efficient review
- Computable analytics

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.



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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