Application of Machine Learning Techniques to Aviation Operations: A Case Study

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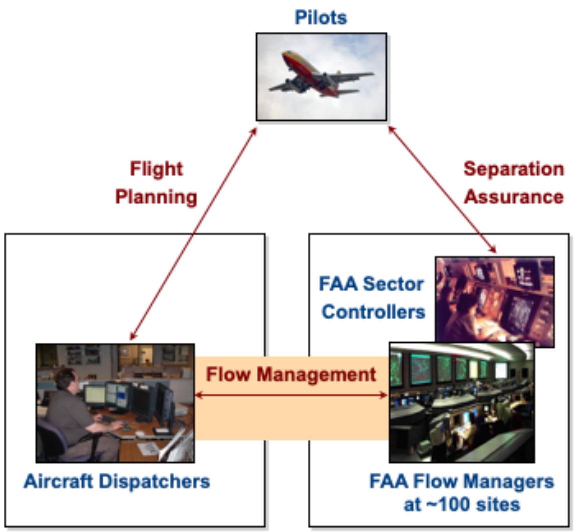
What is this talk about?

- Invited talk in the morning
  - Increasing interest in applying Machine Learning Techniques (MLT) to solve problems in Aviation Operations (AO)
  - Compared physics-based modeling and data driven modeling Review simulation and analysis methods in AO
  - Promises and challenges of applying MLT to AO problems
- NASA case study (2001-2016):

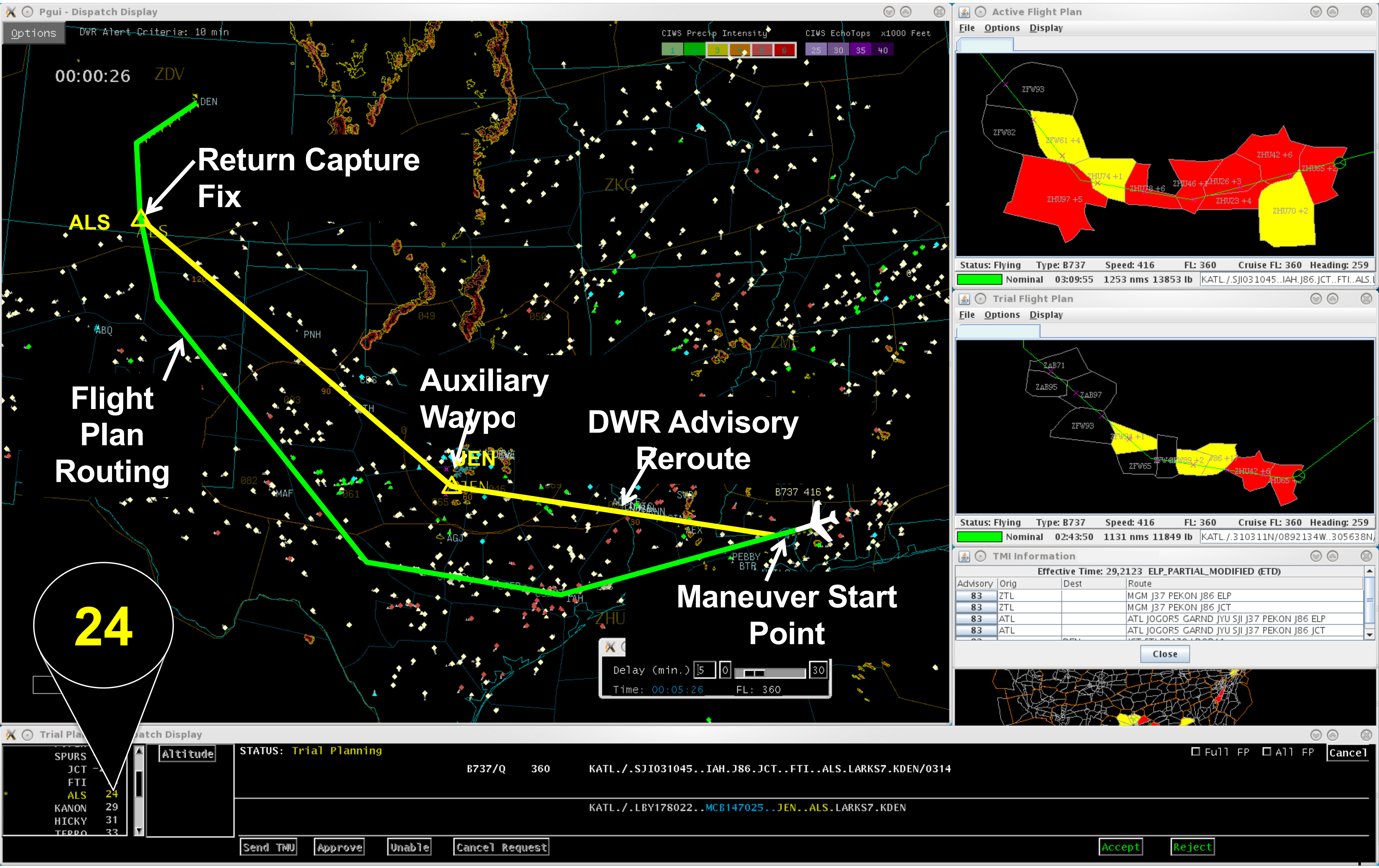
  Direct-To-Tool to Airspace Technology Demonstration (ATD)-3
  - Direct-To Controller Tool
  - Dynamic Weather Routes (DWR)
  - Integrated Multi-Flight Common Routes



Dynamic Weather Routes (DWR)

- Trajectory automation system that continuously and automatically analyzes trajectories of flight en-route
  - Simple modifications to their current routes that can save significant flying time
  - Easily communicated to pilots and air traffic controllers, while avoiding weather and considering traffic conflicts, airspace sector congestion, blocked Special Use Airspace (SUA), and FAA route restrictions
- Users alerted when a route change for a flight can potentially save flight time.
- DWR system was developed with testing at Fort Worth (ZFW) Center in 2012

Dynamic Weather Routes (DWR)



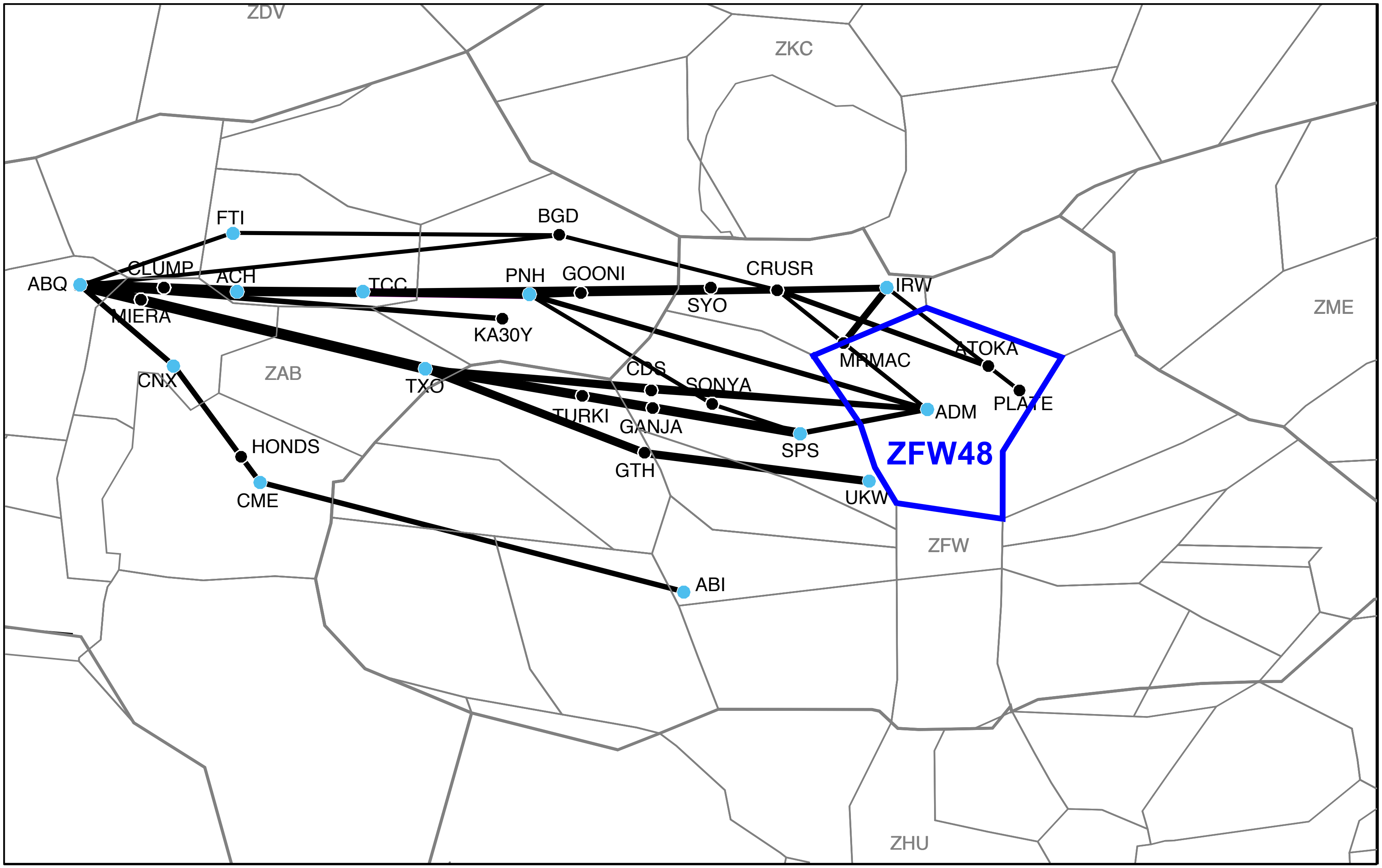
Acceptance of DWR routes

- NASA and American Airlines operational trials indicate actual savings of 3290 flying minutes for 526 American Airlines revenue flights from January 2013 through September 2014
- Route advisories generated by DWR – 78% – were never reviewed by dispatchers, in part for reasons of high workload (in this trial the tool was also not always monitored).
- 65% were rated acceptable by dispatchers
- 38% of the dispatcher accepted routes were rejected by ATC

How to increase Route Acceptability?

- Traditional approach
  - Factors influencing route acceptance
  - Subject-matter-experts
  - Optimization
- Ideal for MLT as there is no knowledge-based model of dispatcher/pilot/controller decision making

Traditional Approach: Building Common Routing Tables of historically used routes



Sample Common Routing Table

Route Start Sector	Via	Final Route Fix	Hist. Count
ZFW48	PNH.TCC.ACH.CLUMP.	ABQ	526
ZFW48	SPS.GANJA.TURKI.TXO.MIERA.	ABQ	373
ZFW48	UKW.GTH.TXO.MIERA.	ABQ	157
ZFW48	TXO.MIERA.	ABQ	109
ZFW48	-	ABQ	101
ZFW48	TCC.ACH.CLUMP.	ABQ	74
ZFW48	PNH.TCC.ACH.	ABQ	54
ZFW48	MRMAC.IRW.CRUSR.GOONI.PNH.TCC.ACH.CLUMP.	ABQ	44
ZFW48	PNH.ACH.	ABQ	37
ZFW48	CRUSR.GOONI.PNH.TCC.ACH.CLUMP.	ABQ	36
ZFW48	ACH.	ABQ	27
ZFW48	ADM.TXO.MIERA.	ABQ	26
ZFW48	GTH.TXO.MIERA.	ABQ	24
ZFW48	ADM.PNH.TCC.ACH.CLUMP.	ABQ	22
ZFW48	ADM.PNH.TCC.ACH.	ABQ	22
ZFW48	ADM.SPS.GANJA.TURKI.TXO.MIERA.	ABQ	21
ZFW48	TXO.	ABQ	17
ZFW48	KA30Y.	ABQ	15
ZFW48	ABI.CME.HONDS.CNX.	ABQ	14
ZFW48	IRW.CRUSR.GOONI.PNH.TCC.ACH.CLUMP.	ABQ	11
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Acceptability Results: ATC Response

Number of Observations In Validation Set (29 days, 2014)		Average number of times routing observed in historical data (April 2015)	
Accepted	Rejected	Accepted	Rejected
198	146	857	117

Route Observed Historically (April 2015)

ATC Response to DWR Route Advisory		True	False
	Accepted	96%	4%
	Rejected	66%	34%

- Accepted data has very high percentage of historically observed routes; necessary not sufficient
- DWR route advisories with increased historical usage can be generated with little reduction in delay savings

Build a predictor of the operational acceptance of reroute requests

- Extract data on route acceptance and rejection for the development of supervised learning algorithms
- Feature Selection
  - Factors that are thought to affect air traffic controller decision making for which data are extracted to define the features
  - Feature identification algorithm to extract a list of significant features
- Identify the data mining algorithms that best fit the extracted data using a model selection algorithm.
- Identify the parameters associated with the chosen data mining algorithm that best fit the extracted data using a parameter selection algorithm.
- Validation of the developed model

Data Availability and Preparation

- One of the biggest challenges when applying data mining techniques to problems in ATM
  - Air traffic controllers and traffic managers use broad range of information for which data may not all be available
  - ATC response to a reroute request: Indirect, based on whether or not the flight had a Center route amendment implemented and recorded within 30 min of its DWR reroute advisory being accepted by the dispatcher.
- Require two classes of data
  - Accepted routes: Recorded, easy to identify
  - Rejected routes: hard, not typically recorded
- Total of 544 observations at American Airlines over 5 months from May 9 through September 30, 2014

Feature Selection

- Factors identified in the literature, and based on Subject Matter Expert (SME) feedback
- Four groups of features impacting air traffic controller acceptance
  - Features describing historical reroute usage (June-August 2015)
    - Historic count (full route), Historic count (by segment)
  - Features describing congestion levels on the proposed reroute
    - Ratio of demand to capacity in reroute starting sector (RSS), RSS over capacity or not at starting time, Number of sectors over capacity, Maximum demand to capacity ratio in all sectors
  - Features describing reroute deviation
    - Number of downstream sectors, Reroute direct to capture fix or not
  - Features describing reroute start point
    - Time to exit RSS, Distance to exit RSS boundary along reroute

Results

- The maximum number of observations included in all steps of the feature selection is 544. Of these 544, 40% are positive (rejected by ATC) and 60% negative (accepted by ATC).
- Number of features reduced to 7 by a greedy search algorithm

1. Hist. Reroute Count by Segment;
2. Time to Exit RSS;
3. No. Downstream Sectors;
4. Direct Route;
5. Dist. to Exit RSS;
6. RSS D/C Ratio; and
7. RSS Over Capacity.

Model Selection

	Logistic Regression	Decision Tree	SVM	Random Forest	Adaboost
Accuracy	0.732	0.735	0.685	0.817	0.776
Misclassification Error	0.268	0.265	0.315	0.183	0.224
True Positive Rate	0.711	0.750	0.632	0.842	0.763
True Negative Rate	0.752	0.721	0.733	0.794	0.788
Precision	0.725	0.713	0.686	0.790	0.768
F-Score	0.718	0.731	0.658	0.815	0.766
Area under ROC Curve	0.818	0.767	0.770	0.886	0.864

- Random Forest (RF) and Adaboost performed best based on F-score: (0.815, 0.766)
- Number of trees in RF was varied from 20 to 100 and tree size 40 maximizes the F-score.
- RF Model performance is reasonable using10-fold cross validation
  - F-Score (0.767), Accuracy (0.744),TPR (0.875)

Challenges in Applying MLT

- Availability of training data
  - Security, Regulatory and Proprietary issues
  - Appropriateness of available data to the task
  - Imbalanced datasets
- Feature selection
  - Expert opinion, reduction of problem size
- Selection of a learning method
  - Classification, regression, supervised, unsupervised, accuracy, interpretation of results
  - No single algorithm is best for all tasks
- Balance between overfitting and underfitting
- Performance evaluation
  - 10-fold cross-validation; natural split in data

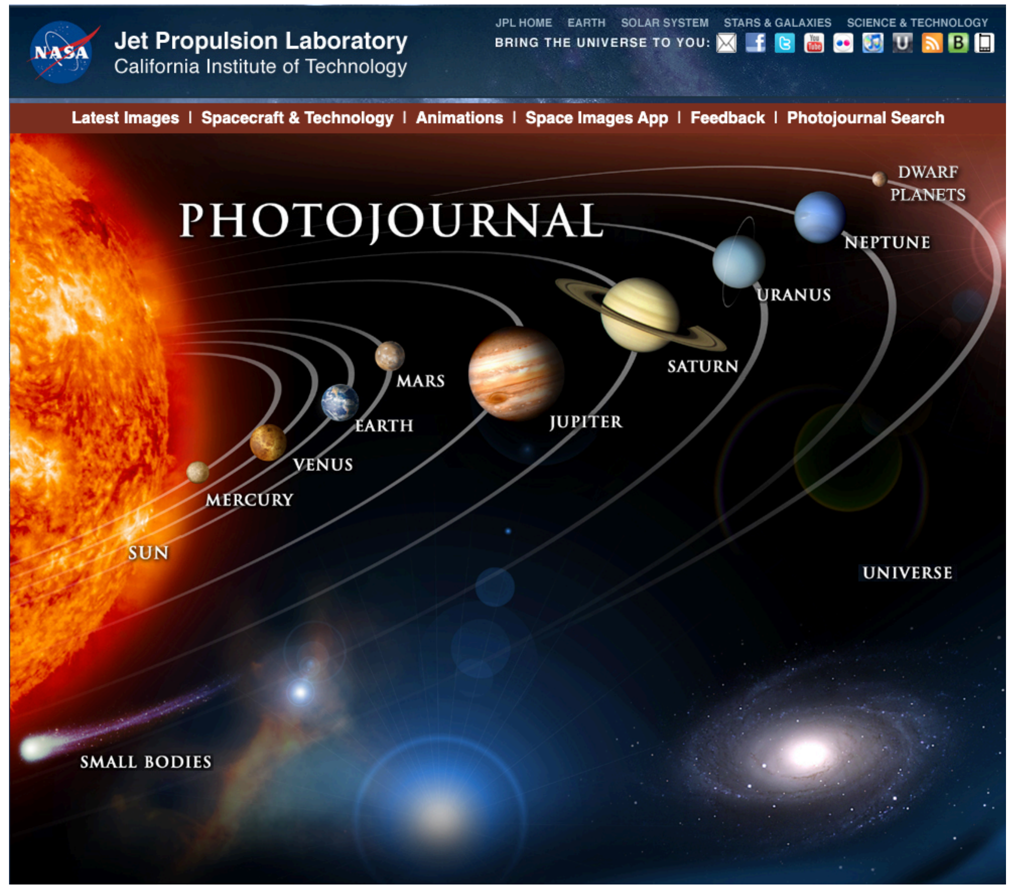
Concluding Remarks

- Presented issues to be addressed in applying MLT to a decision-making problem in AO
- MLT provides a new class of tools
  - Method of choice in the absence of physics-based models
  - No single ML algorithm is best for all applications
  - Feature selection plays a key role
- More research needed on performance evaluation of MLT for critical tasks
- Task, prior knowledge, data: key to modeling approach

Applications from literature

Application	Data	MLT	Remarks
NAS Performance Metrics	OPSNET, ASPM Convective Weather (2005-2008)	LR,MLR, FFNN	FFNN performed better than MLR
	BTS data (2011-12) Hourly delays 1107 O-D pairs between 14 airports	MJLS, CART, NN	NN and MLJS performance varied with task
Anomaly Detection	Boeing 777 aircraft data 365 flights between 14 airports	Density based clustering algorithm	Identified outliers during take-off and landing Poor sensitivity to short duration anomaly
Conflict detection And resolution	Mode-S data covering France 21314 aircraft trajectories with 8 parameters (position, speed,..)	MLR, SVM, FFNN GBM, RF	MLT performed better than baseline; GBM performed best
	Randomly generated conflict data 15 aircraft in 100nm diameter circle	RL	RL identified 81% of the conflicts under uncertainty
ATC decision Making	Accepted/rejected DWR test data at American Airlines May-September 2014	Logistic Regression SVM, CART, RF Adaboost	RF and Adaboost performed best
	8760 Hourly observations during 2012 LAMP, GDP, NTML, RUC, ASPM	Logistic Regression Decision Trees	MLT identified different types of weather days similar GDP days

Johannes Kepler (1571-1630)



"Johannes Kepler 1610," Artist unknown, https://commons.wikimedia.org/wiki/File:Johannes_Kepler_1610.jpg, Public domain.