ML Airport Surface Model

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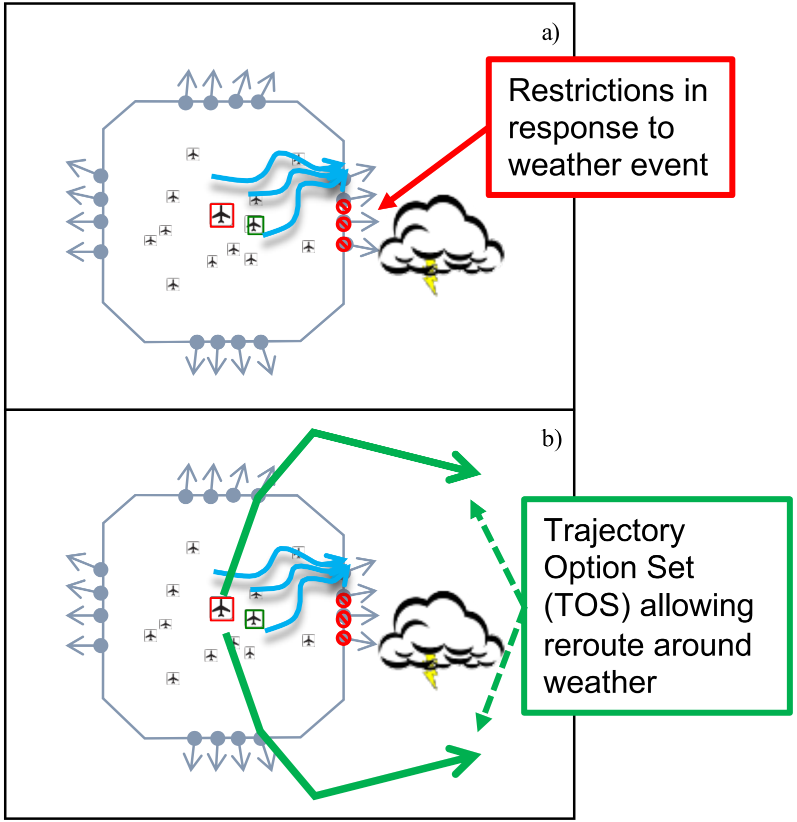
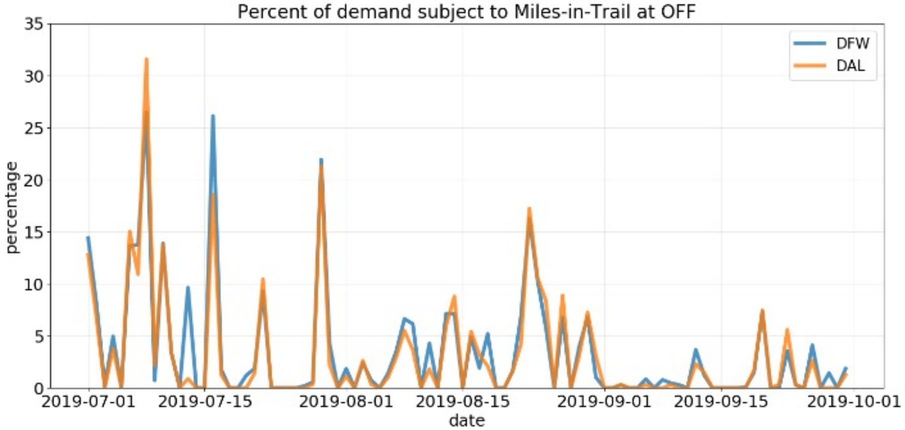
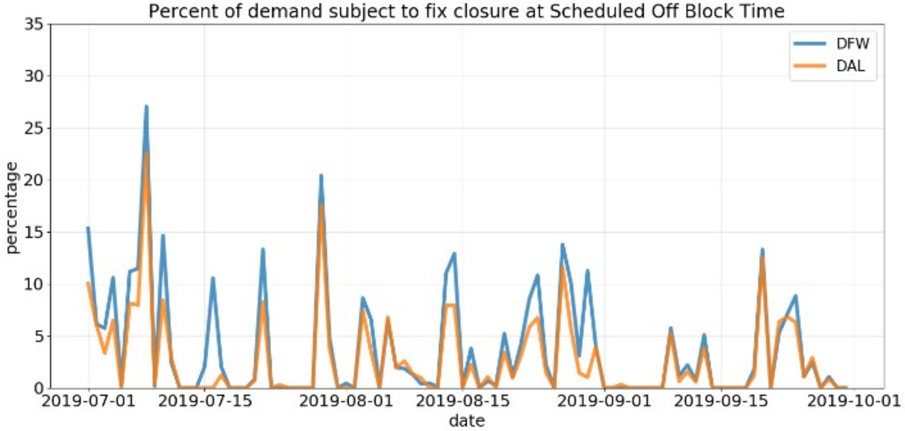
ML Airport Surface Model Outline

- What?
- Why?
- How?
- Validation

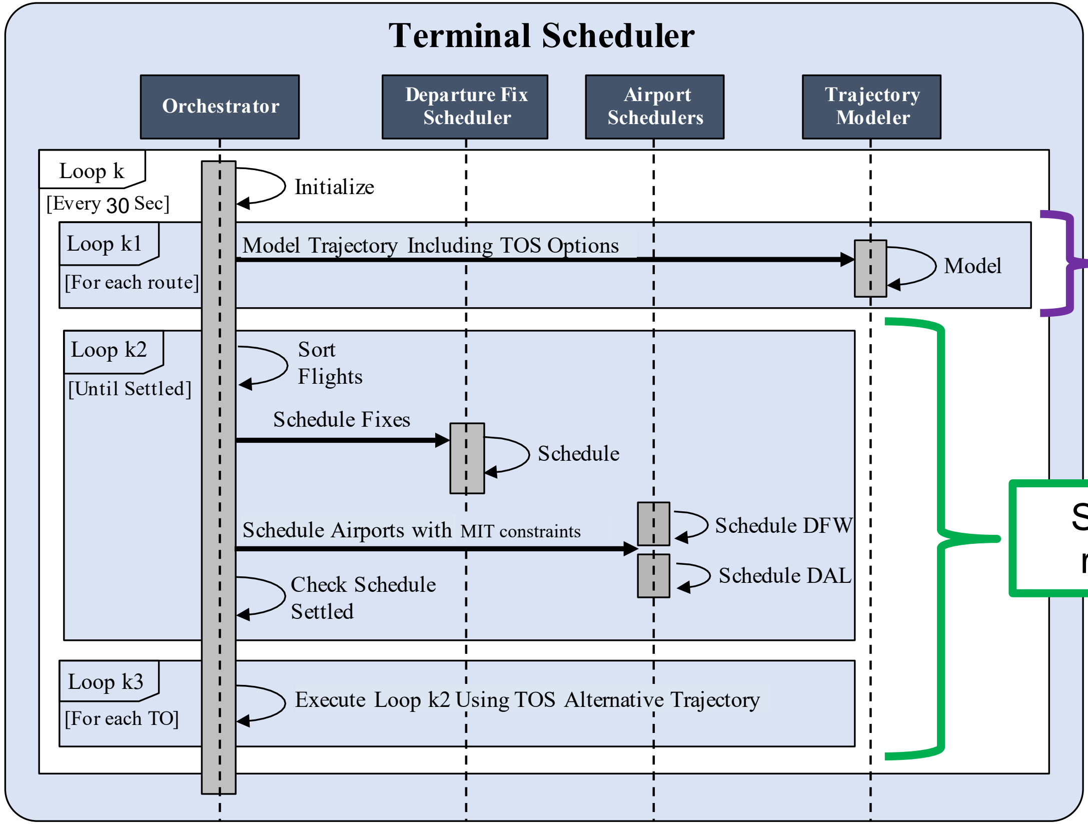
Trajectory Option Set (TOS) Pre-departure Reroute Capability Running in North Texas Metroplex







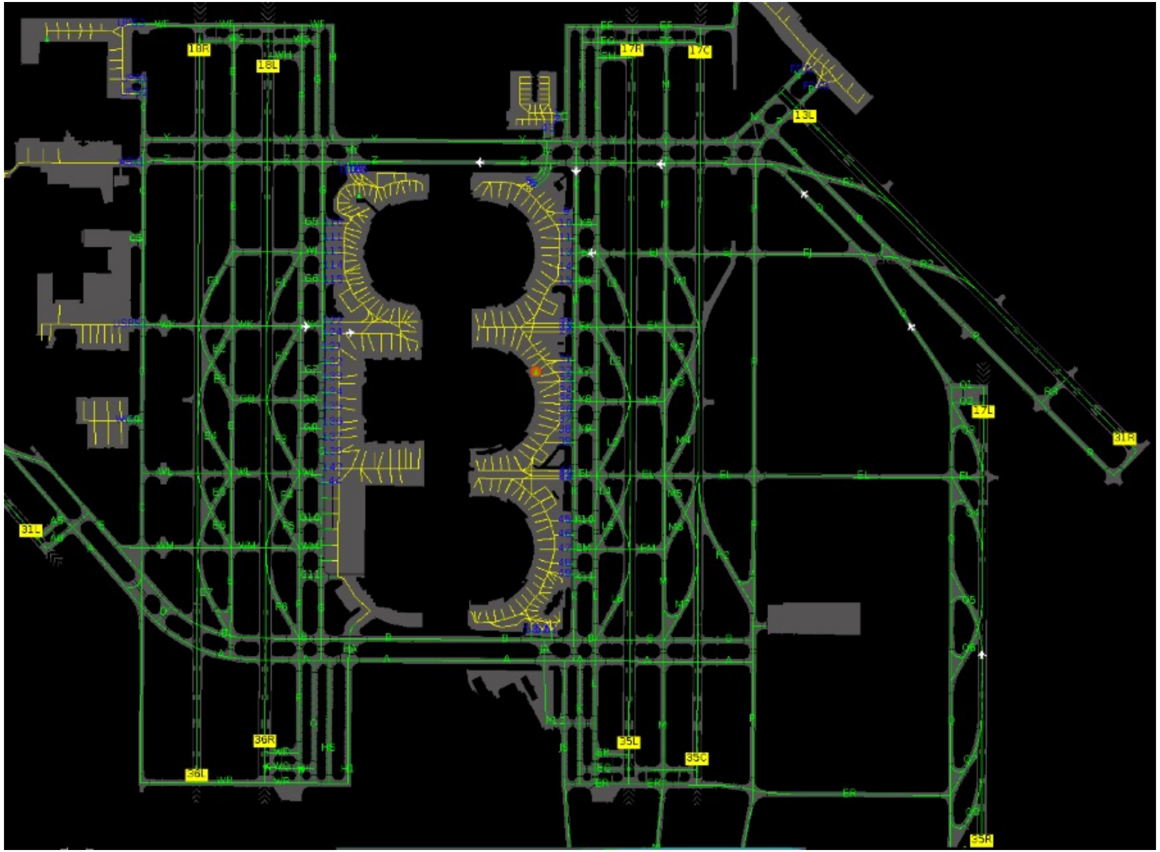
Metroplex Scheduling Algorithm



Modelling unimpeded trajectory requires significant adaptation

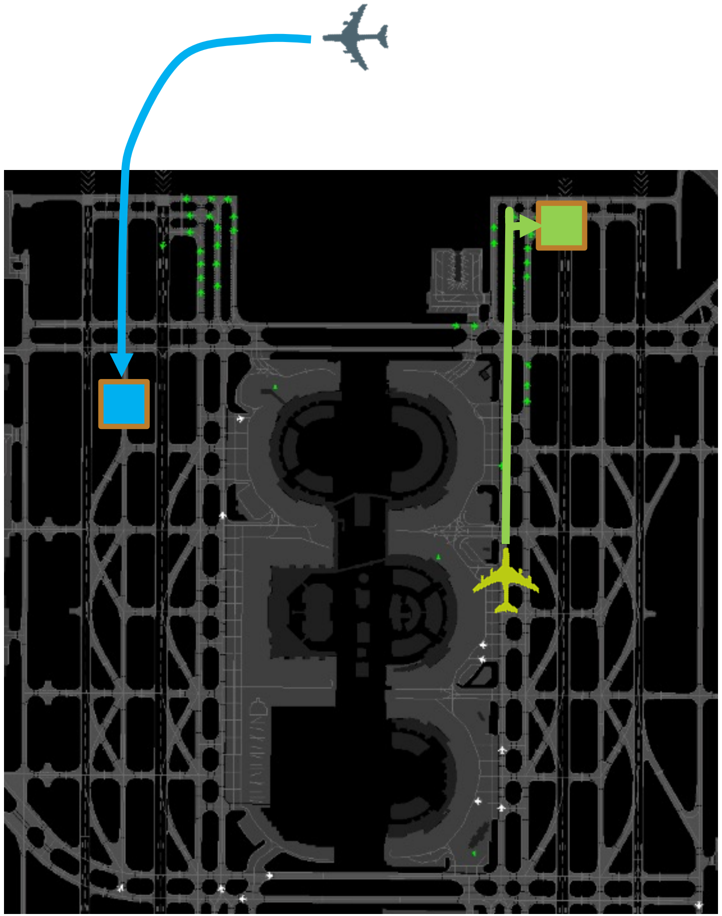
Scheduling at constraint points requires little to no adaptation

DFW Airport Adaptation Example



- Detailed link node network defines the airport surface structure including gate locations, runway locations, and taxi routes
- Adaptation goes beyond physical structure to include SME knowledge encoded in decision trees (for example the fix to runway mappings)
- Requires significant time and effort to build and maintain for each airport

Machine Learning Airport Surface Model



Airport configuration

Departure

- Runway
- Unimpeded Take OFF Time
- Unimpeded Fix Crossing Time

Arrival

- Runway
- Estimated ON Time

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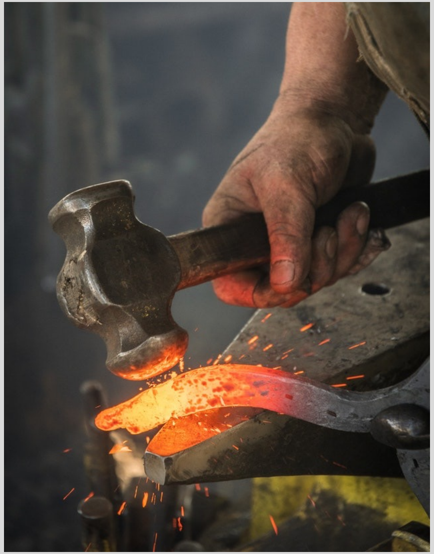
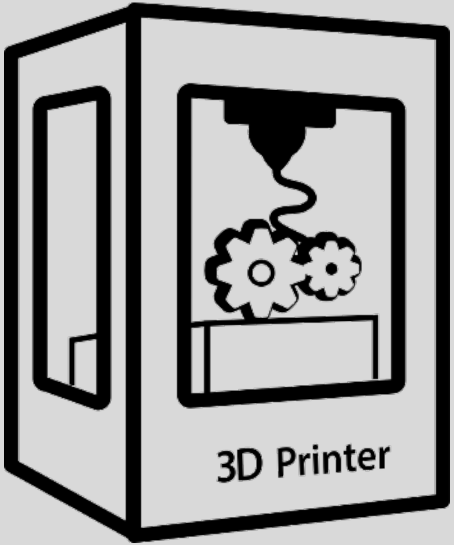
Machine Learning Provides Scalability

Traditional Methods



- Good at specific tasks (airports)
- Requires detailed knowledge
- Continuous maintenance

Machine Learning



- Flexible to new tasks (airports)
- Learns detailed knowledge
- Semi-automated maintenance

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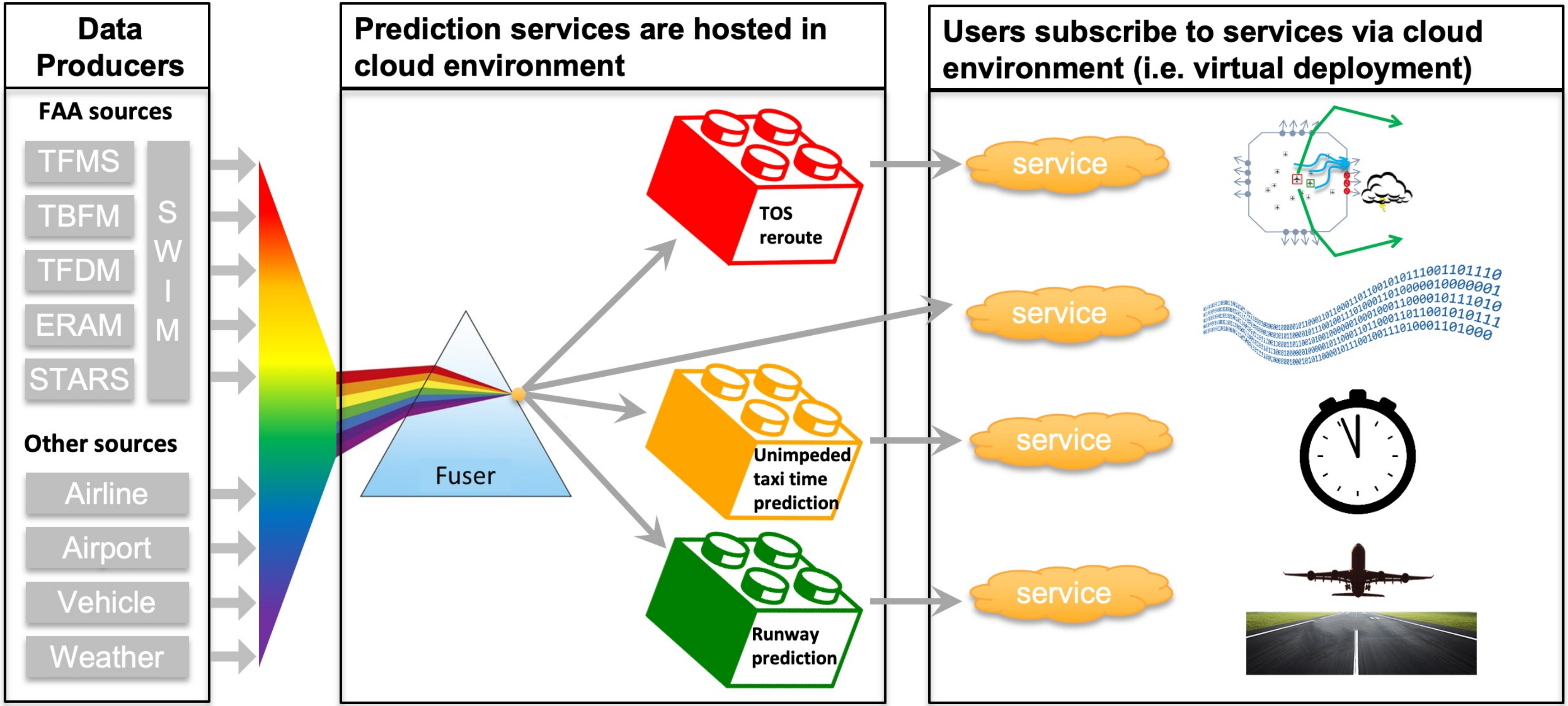
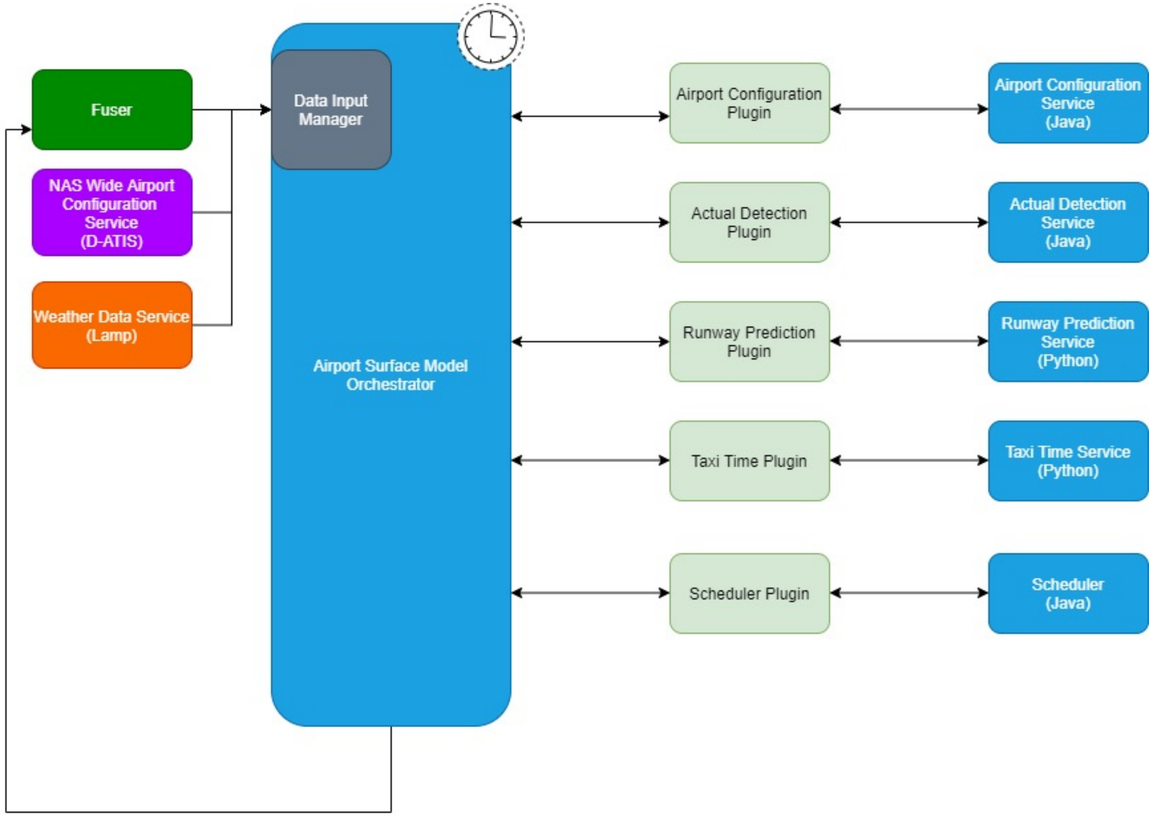
Real-time ML Services Powered by SWIM

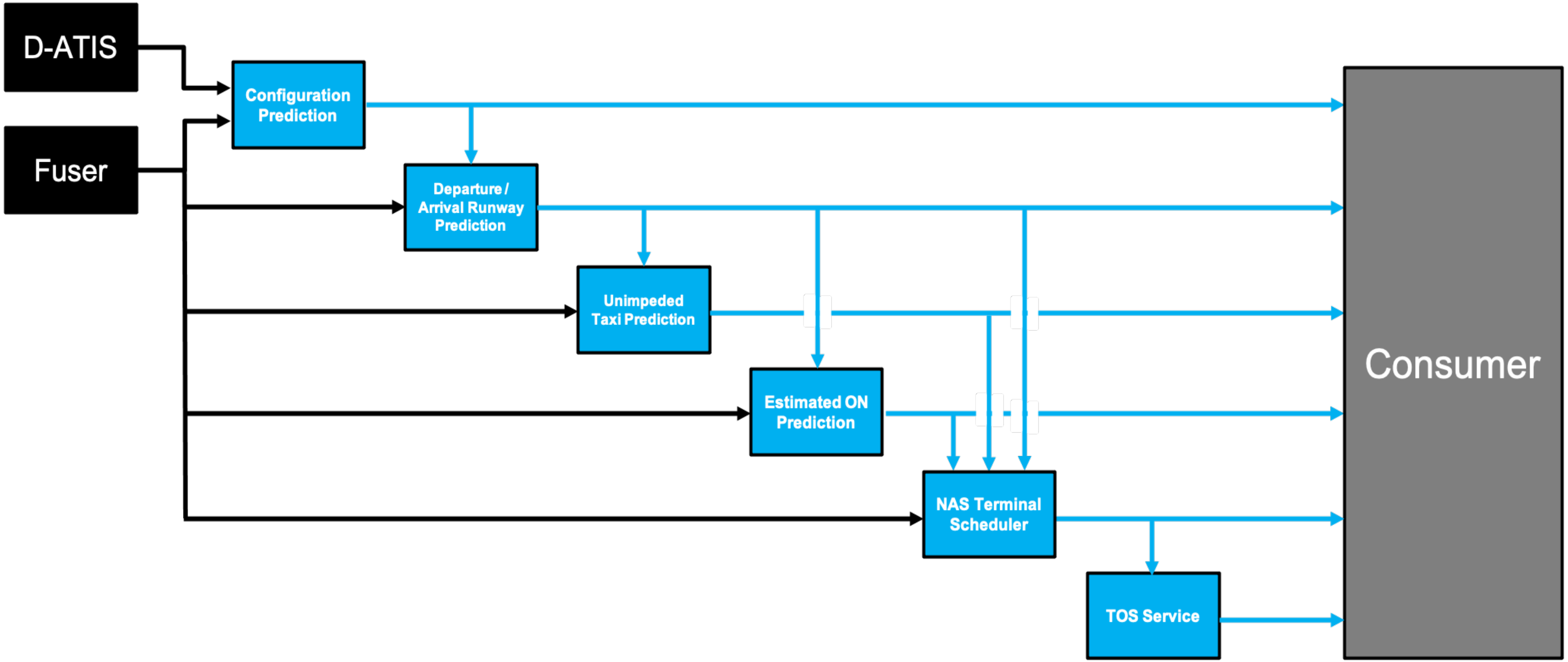


Airport Surface Model Orchestration



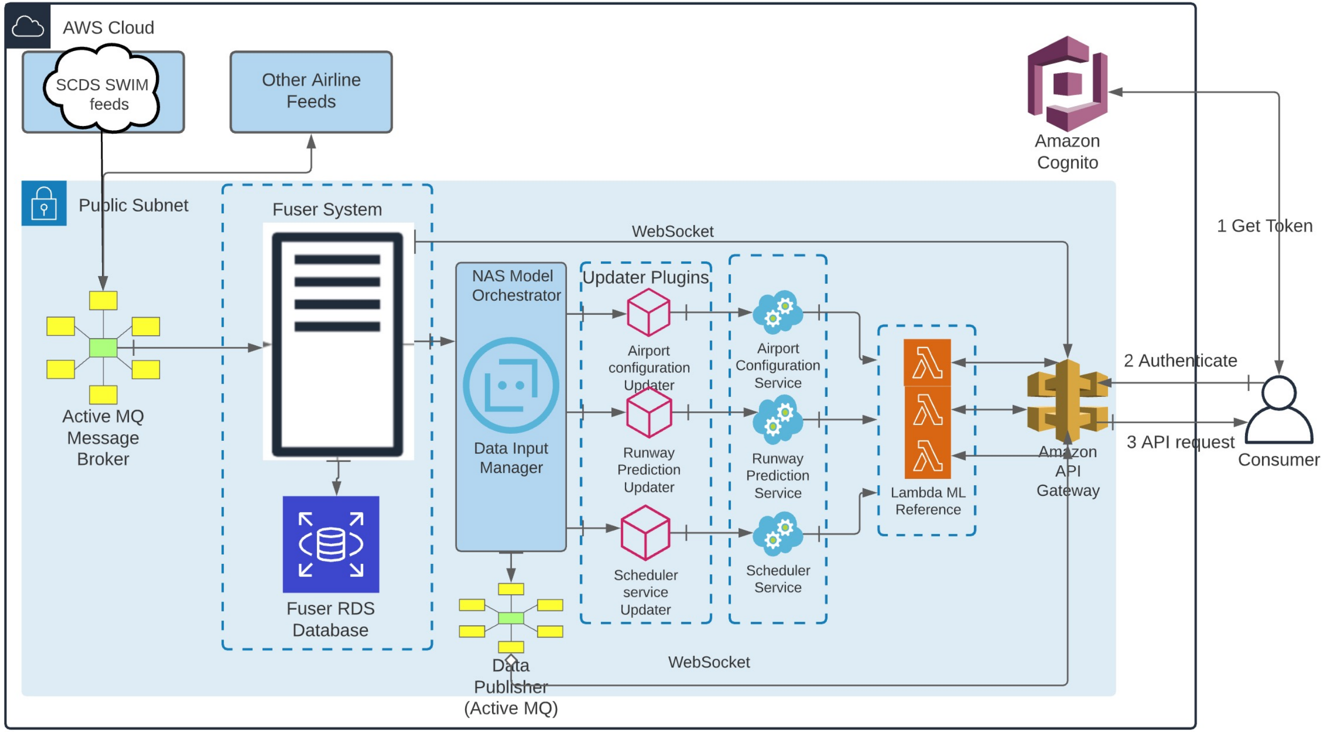
- Airport Surface Model Orchestrator gathers inputs and controls the order of execution
- Services run independently
- Using a mix of Java and Python services

Relationship Between Prediction Services



ML services can be dependent on other services, e.g., the Unimpeded Taxi Out Prediction requires the Departure Runway Prediction

Future Work: AWS Cloud Deployment



Airport Surface Model Orchestrator with service-based architecture designed with AWS cloud deployment in mind

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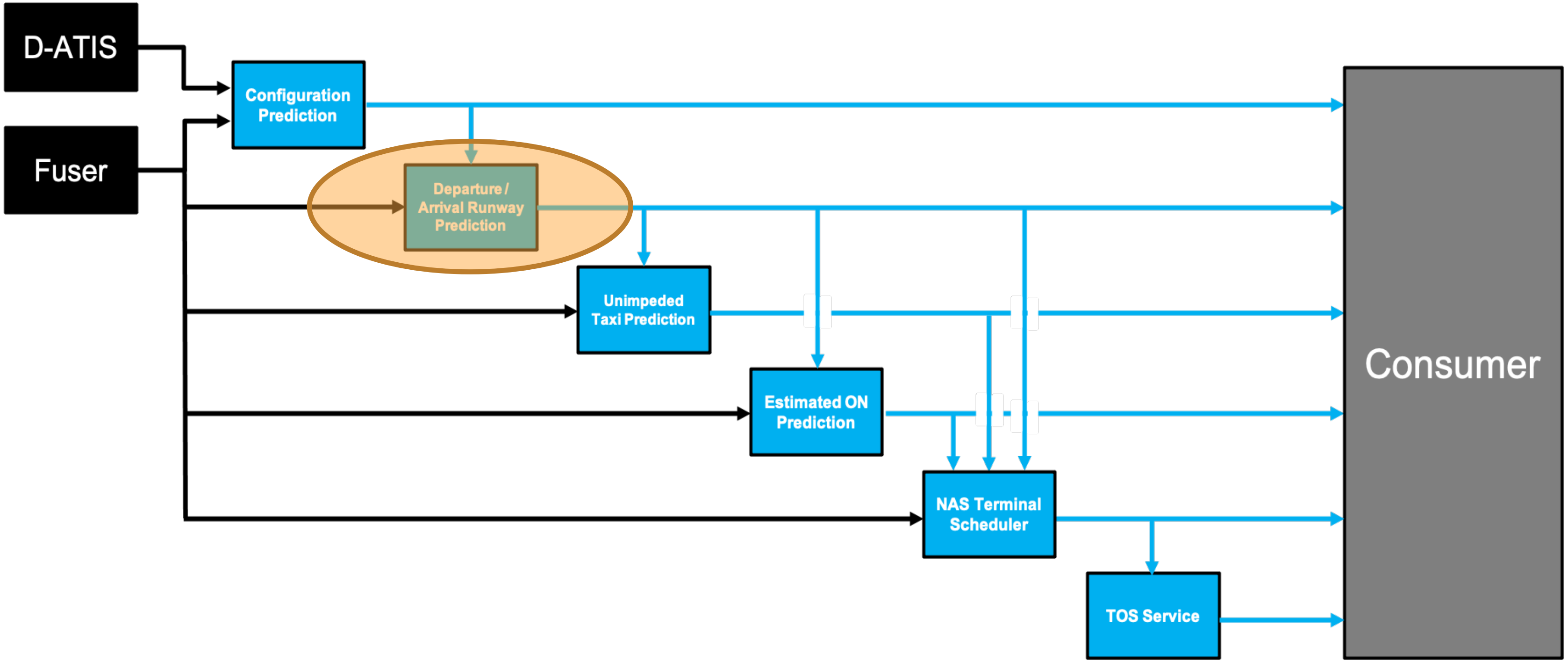
ML Departure and Arrival Runway Validation



- Departure runway validation sampled with prediction from OUT event
- Arrival runway validation sampled with prediction 30 minutes prior to ON

KDFW Runway Model Accuracy

ML KDFW Departure Runway

Confusion Matrix for DFW Test Data

True Runway \ Predicted Runway	13L	17C	17L	17R	18L	18R	31L	31R	35C	35L	36L	36R
13L	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
17C	0.0%	0.2%	0.0%	0.1%	0.1%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
17L	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
17R	0.0%	0.0%	0.0%	33.6%	5.1%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
18L	0.0%	0.0%	0.0%	1.9%	26.5%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
18R	0.0%	0.0%	0.0%	0.1%	0.0%	0.1%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
31L	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.1%	0.0%	0.1%
31R	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.2%	0.0%	0.0%	0.0%	0.0%
35C	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.1%	0.1%	0.0%	0.0%
35L	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	13.6%	0.0%	2.0%
36L	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
36R	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	1.5%	0.0%	14.5%

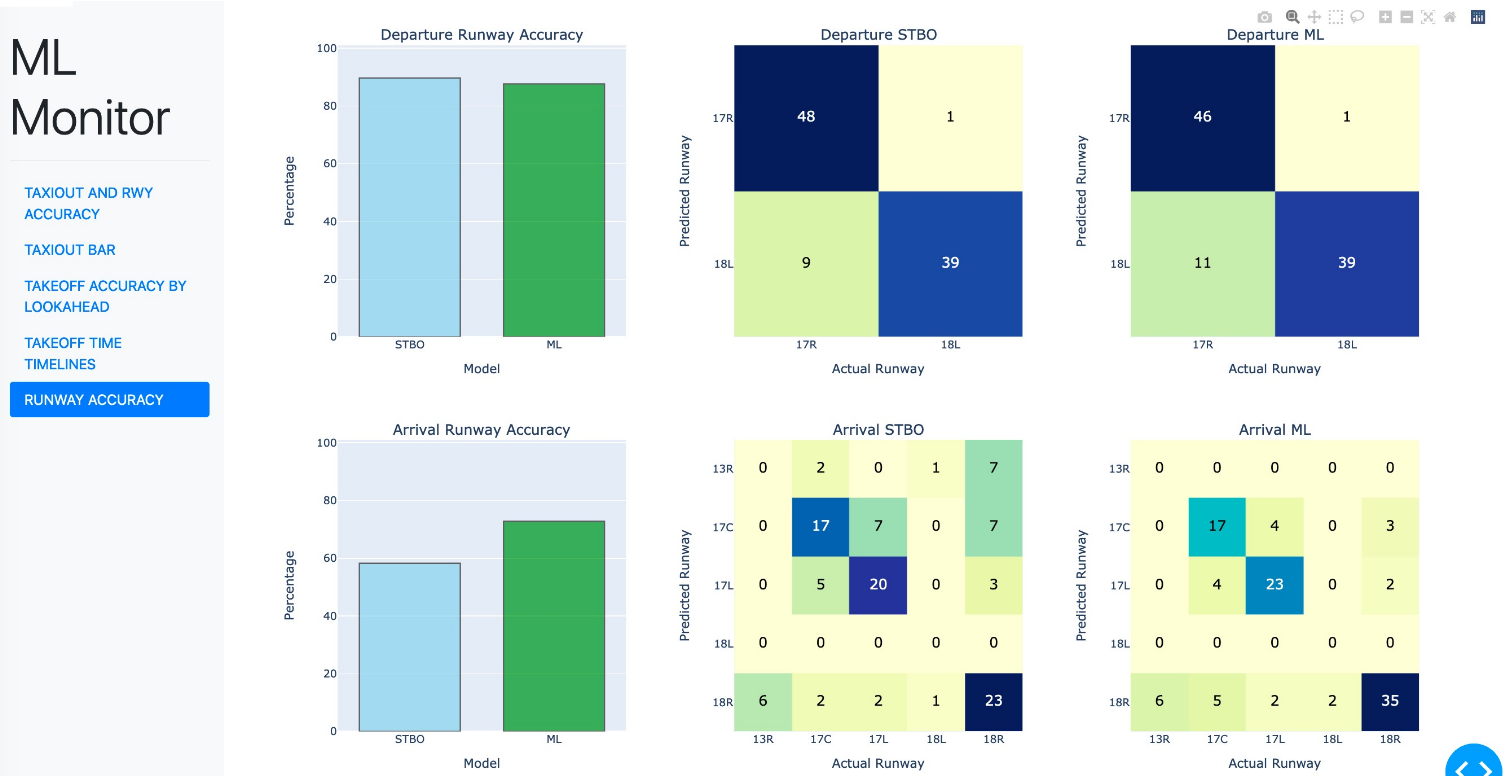
ML KDFW Arrival Runway

Confusion Matrix for DFW Test Data

True Runway \ Predicted Runway	13R	17C	17L	17R	18L	18R	31L	31R	35C	35L	35R	36L	36R
13R	2.9%	1.3%	0.4%	0.0%	0.0%	3.7%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
17C	1.8%	15.1%	5.7%	0.1%	0.4%	4.8%	0.0%	0.0%	0.1%	0.0%	0.0%	0.0%	0.0%
17L	0.1%	3.7%	13.6%	0.0%	0.0%	0.7%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
17R	0.0%	0.5%	0.1%	0.1%	0.0%	0.2%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
18L	0.2%	0.9%	0.2%	0.0%	1.2%	0.3%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
18R	0.1%	2.0%	0.9%	0.0%	0.1%	14.9%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
31L	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.2%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
31R	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	1.2%	0.1%	0.0%	1.2%	0.1%	0.0%
35C	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.2%	5.4%	0.0%	1.6%	1.2%	0.0%
35L	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.1%	0.0%	0.0%	0.0%	0.0%
35R	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.4%	1.7%	0.0%	4.0%	0.3%	0.0%
36L	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.7%	0.0%	0.4%	3.6%	0.0%
36R	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.6%	0.0%	0.1%	0.1%	0.3%

ML departure runway accuracy 88% and arrival runway accuracy 62%

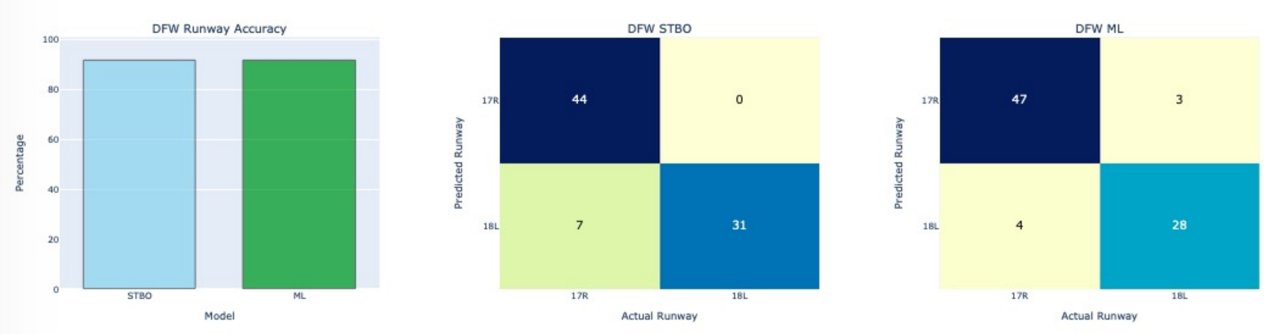
KDFW Runway Model Accuracy



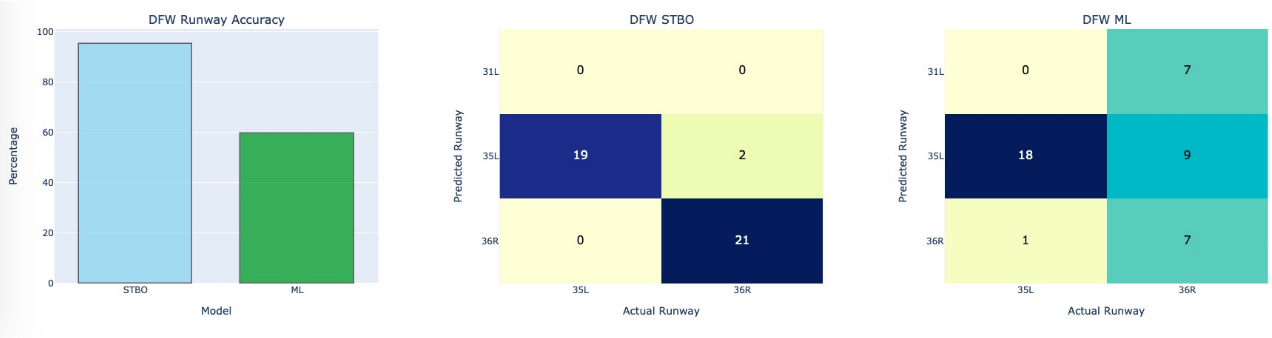
- ML arrival runway can outperform STBO decision trees
- ML departure runway can be comparable to STBO decision trees

KDFW Departure Runway Accuracy

KDFW Departure South Flow



KDFW Departure North Flow



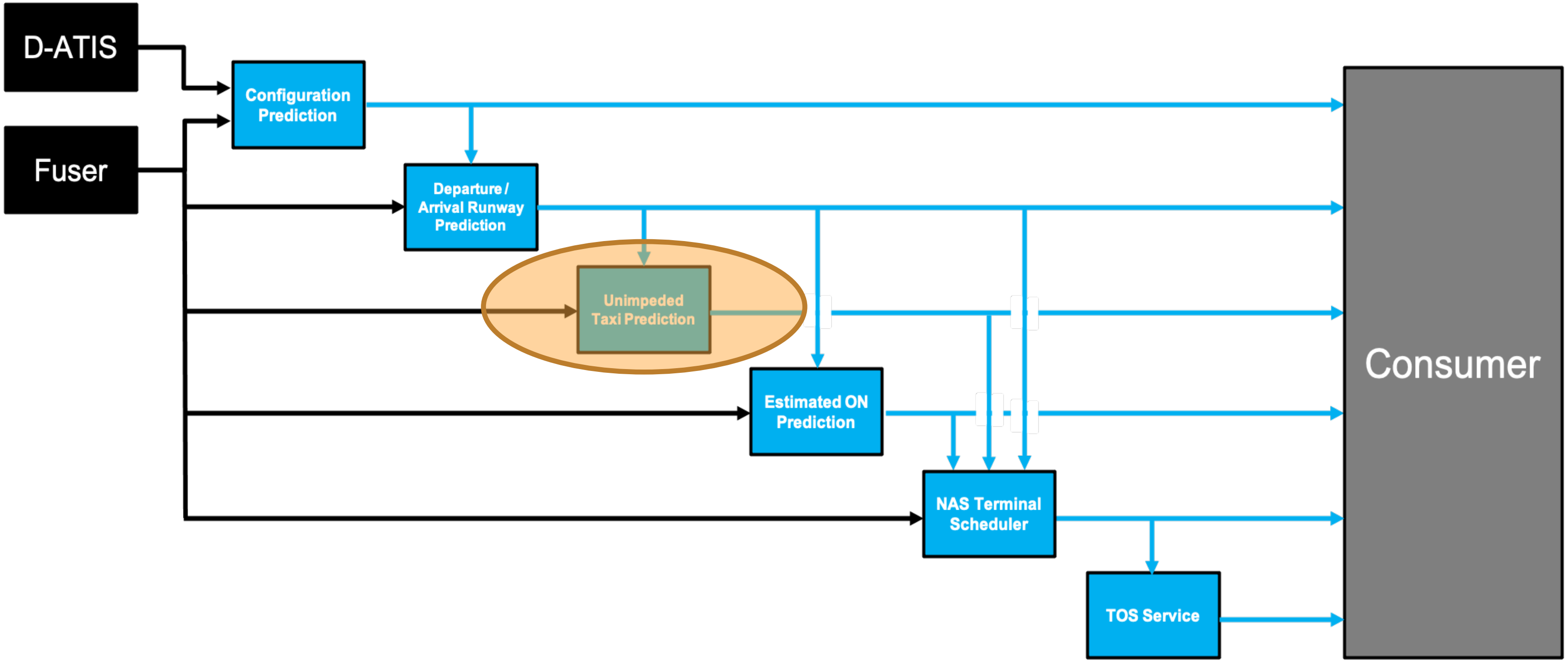
Early testing showed that ML departure runway performance can be sensitive to ”states” of the system and context of the data (runway closure)

Example of D-ATIS Data Quality

in_config	airport_configuration_name	num_not_in_config	num_in_config	count	fraction_in_config
	D_17C_17R_18L_18R_A_17C_17R_18L_18R	0.0	216.0	216.0	1.000000
	D_17C_17R_18L_A_13R_17C_17L	0.0	8692.0	8692.0	1.000000
	D_17C_17R_18L_A_13R_17C_17L_18L	0.0	9282.0	9282.0	1.000000
	D_17C_17R_18L_A_13R_17C_17R_18L_18R	0.0	6735.0	6735.0	1.000000
	D_17C_17R_18L_A_17C	0.0	182.0	182.0	1.000000
	D_17C_17R_18L_A_17C_17L	0.0	183.0	183.0	1.000000
	D_17C_17R_18L_A_17C_17R_18L	0.0	192.0	192.0	1.000000
	D_17C_17R_18L_A_17C_17R_18R	0.0	1385.0	1385.0	1.000000
	D_17C_17R_A_17C	0.0	124.0	124.0	1.000000
	D_17C_18L_18R_A_17C_18R	0.0	247.0	247.0	1.000000
	D_17C_18L_A_13R_17C_17L	0.0	204.0	204.0	1.000000
	D_17C_18L_A_13R_17C_17L_18R	227.0	446.0	673.0	0.662704
	D_17C_18L_A_17C	3144.0	2191.0	5335.0	0.410684
	D_17C_18L_A_17C_17L	0.0	249.0	249.0	1.000000
	D_17C_18L_A_17C_17L_18L	0.0	813.0	813.0	1.000000
	D_17C_18L_A_17C_17L_18L_18R	0.0	178.0	178.0	1.000000
	D_17C_18L_A_17C_18L	646.0	8426.0	9072.0	0.928792
	D_17C_18L_A_17C_18L_18R	224.0	642.0	866.0	0.741339
	D_17C_18L_A_17C_18R	214.0	323.0	537.0	0.601490

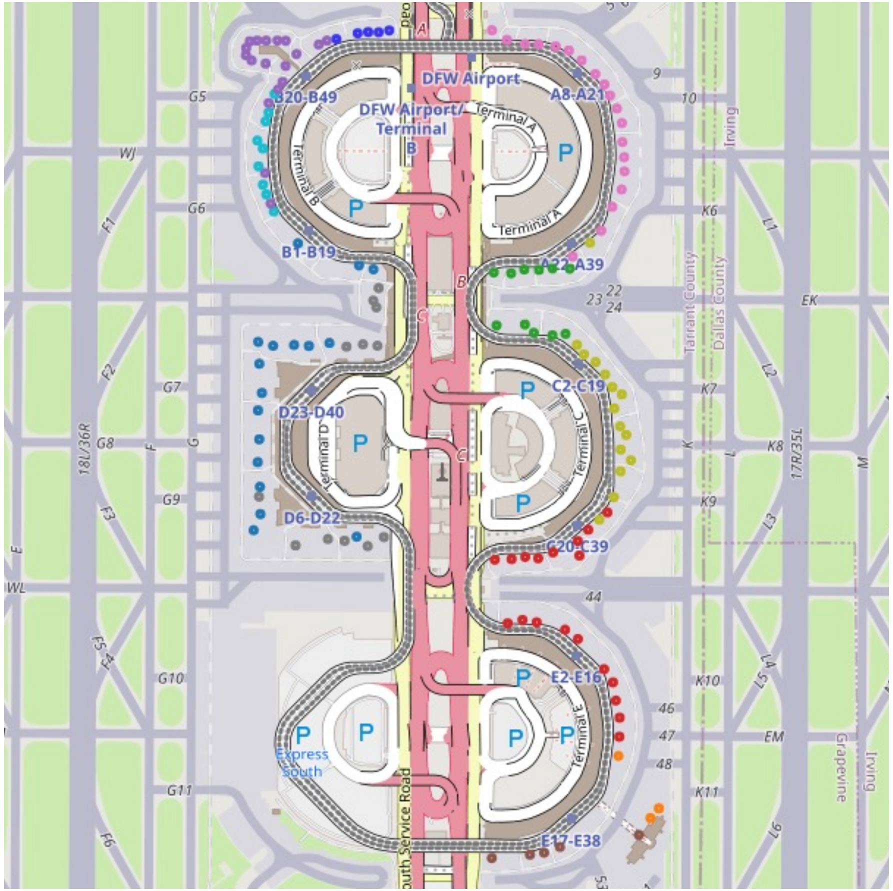
D-ATIS configuration not always representative of actual operations

ML Unimpeded Taxi Out Validation



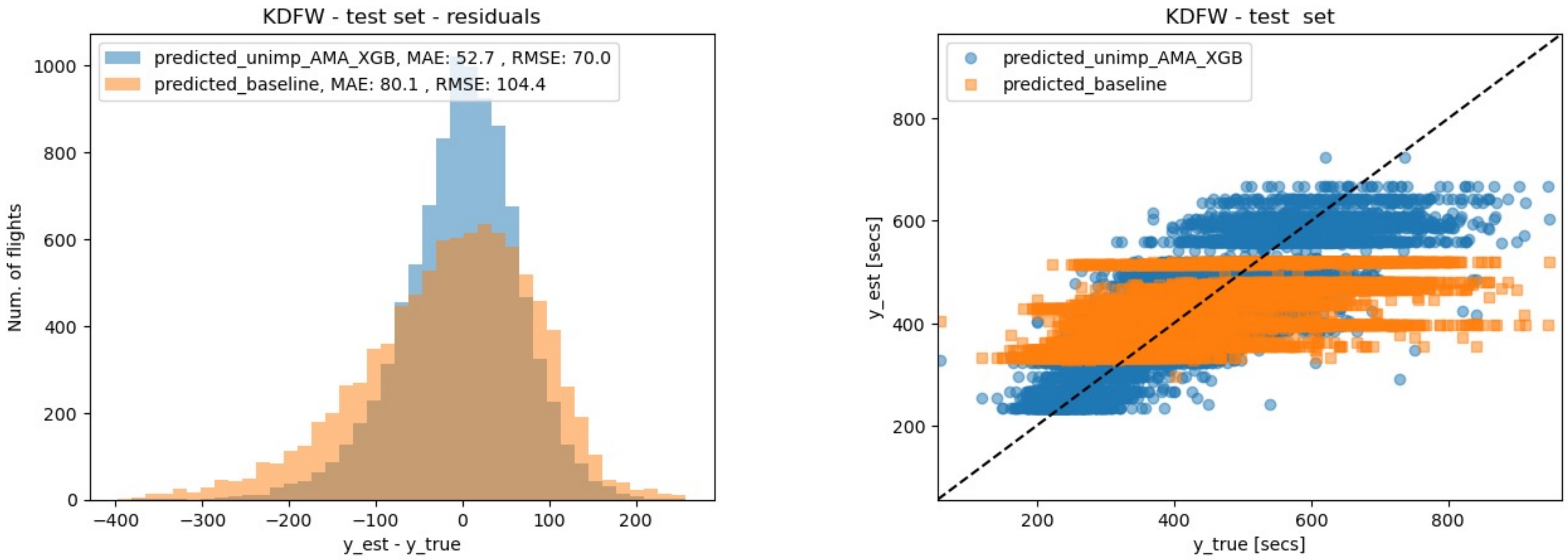
Validation by comparison to (1) the true taxi time for 'unimpeded' flights and (2) the STBO prediction of unimpeded taxi out duration

Departure Gate Clustering



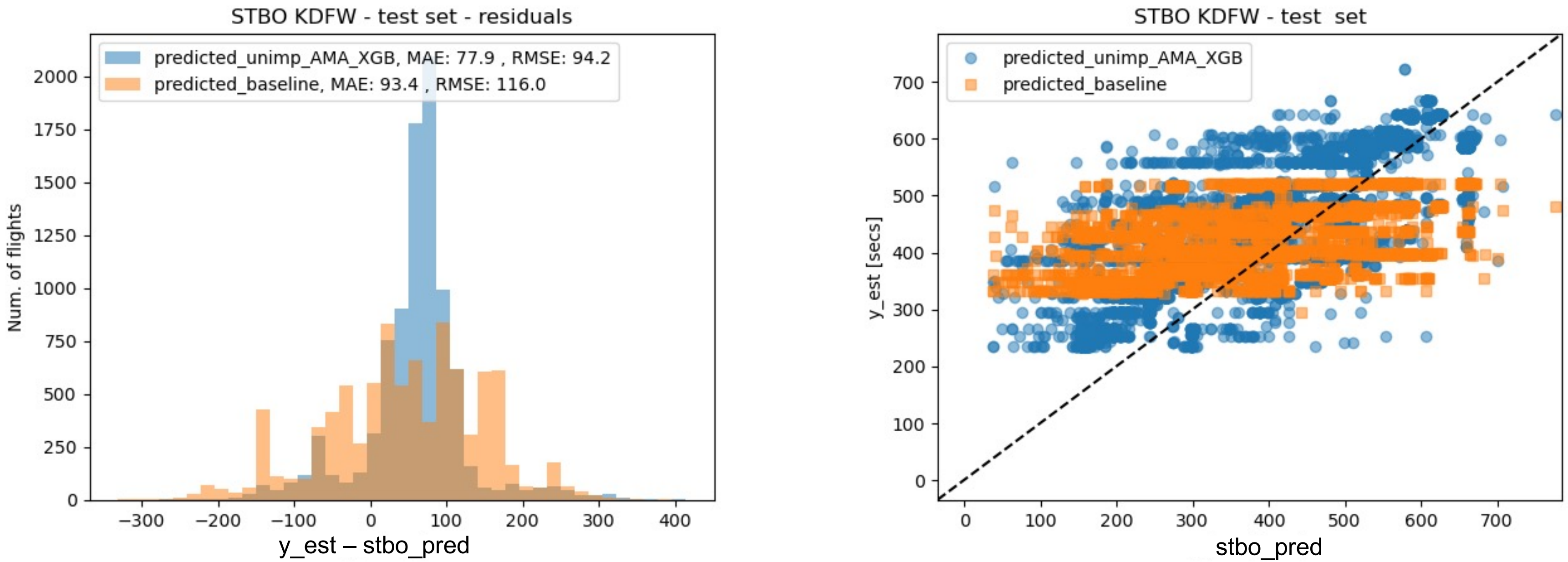
- Gate clusters used as features for the ML unimpeded taxi out
- Adaptation free approach to gate clustering without any knowledge of physical location
- Number of clusters chosen to minimize median absolute deviation of residuals with actual taxi time

ML Unimpeded AMA Taxi Out Validation



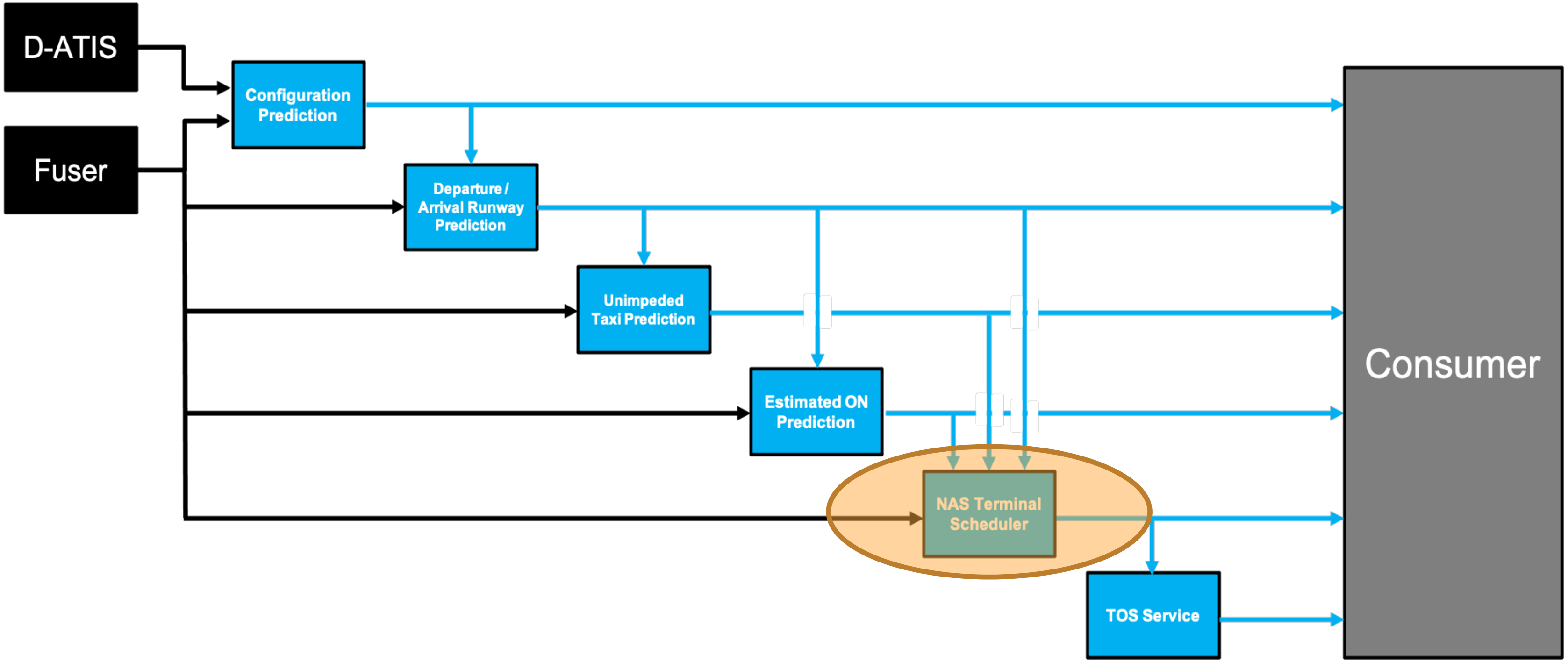
- Validation against the true taxi time for ‘unimpeded’ flights
- ‘Unimpeded’ flights maintain minimum velocity threshold in AMA
- Orange baseline prediction is average of flights with same terminal/runway

ML Unimpeded AMA Taxi Out Validation



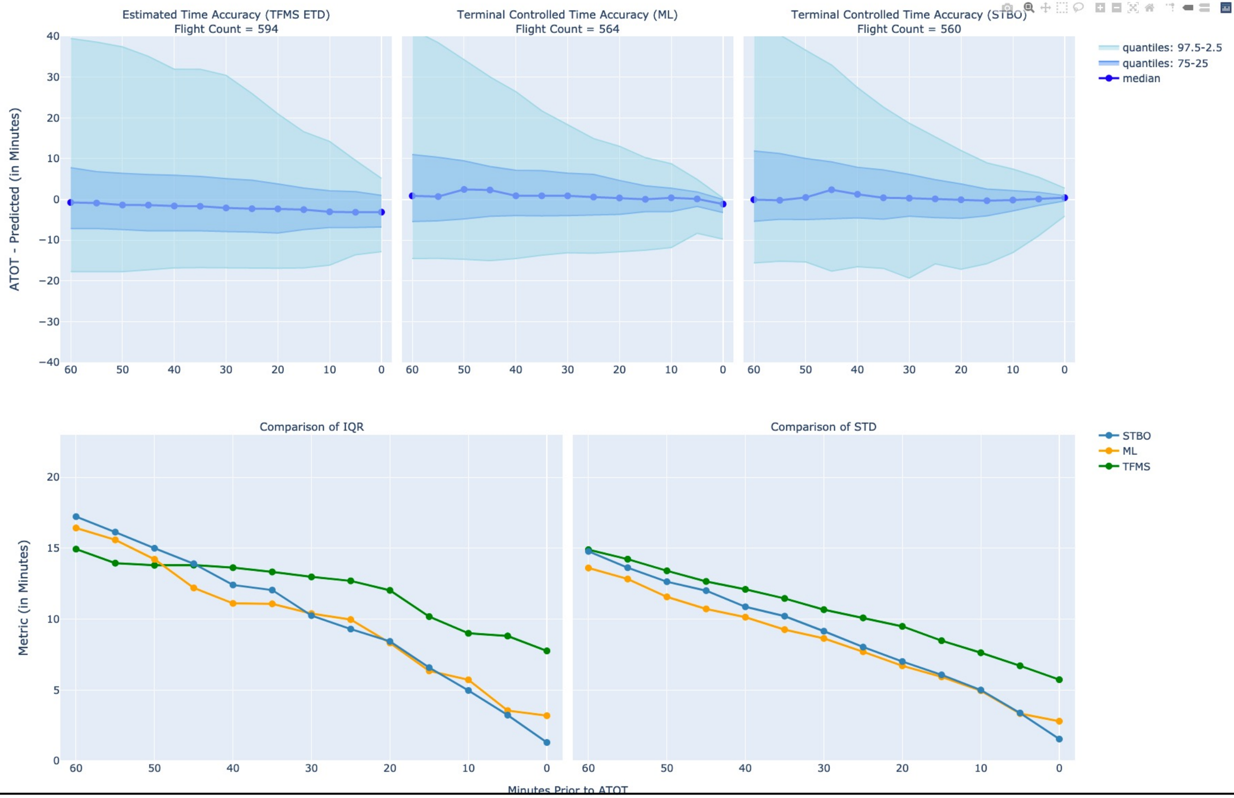
- Validation against the STBO predicted unimpeded AMA taxi out
- STBO unimpeded prediction based on adaptation and physics based model
- Orange baseline prediction is average of flights with same terminal/runway

NAS Terminal Scheduler Validation



Validation of Estimated Take Off Time accuracy as a function of lookahead

KDFW Estimated Take Off Time Accuracy



- ML and STBO Estimated Take Off Time (ETOT) outperform TFMS ETD
- ML and STBO show similar ETOT accuracy

Summary

- ML Airport Surface Model provides opportunity to replace adaptation based physical models
- Airport Surface Model Orchestrator gathers real-time inputs and controls order of execution of ML models
- ML models have dependencies from other predictions and the overall performance can be sensitive to particular models (runway model)
- Early results are encouraging for ML model performance and Estimated Take Off Time accuracy

Questions?

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