An Optimization of Airport Surface Congestion to Minimize Taxi Times

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Improving Operational Efficiency of the NAS

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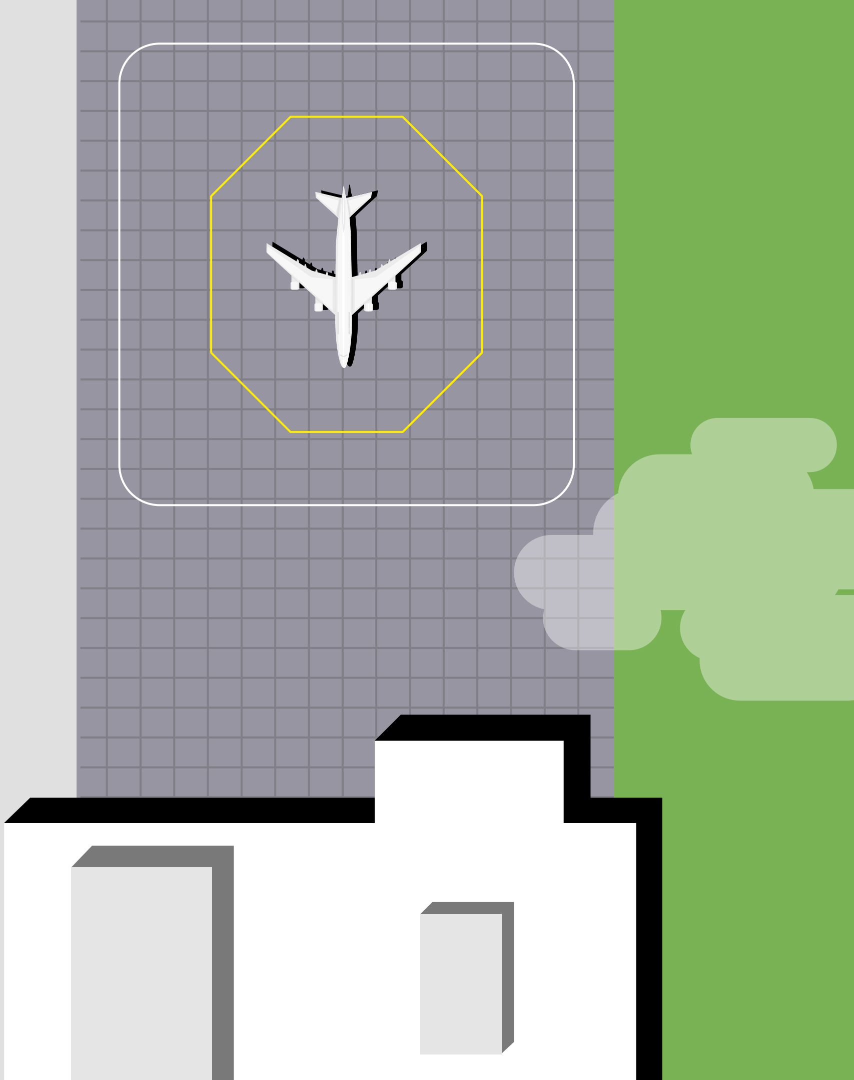
01

Motivation

What benefit does the project provide?

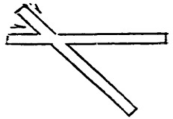


Delays are Costly, and the Runway is Constrained

Total Cost of Delay in the U.S. (dollars, billion)

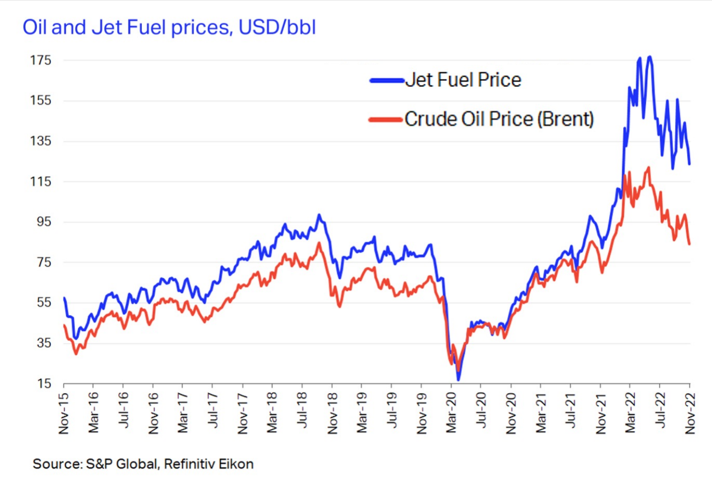
	2016	2017	2018	2019
Airlines	5.6	6.4	7.7	8.3
Passengers	13.3	14.8	16.4	18.1
Lost Demand	1.8	2.0	2.2	2.4
Indirect	3.0	3.4	3.9	4.2
Total	**23.7**	**26.6**	**30.2**	**33.0**

FAA, 2019

NO.	Runway-use Configuration	Mix Index %(C+3D)	Hourly Capacity Ops/Hr VFR	Hourly Capacity Ops/Hr IFR	Annual Service Volume Ops/Yr
9.		0 to 20	98	59	230,000
		21 to 50	77	57	200,000
		51 to 80	77	56	215,000
		81 to 120	76	59	225,000
		121 to 180	72	60	265,000

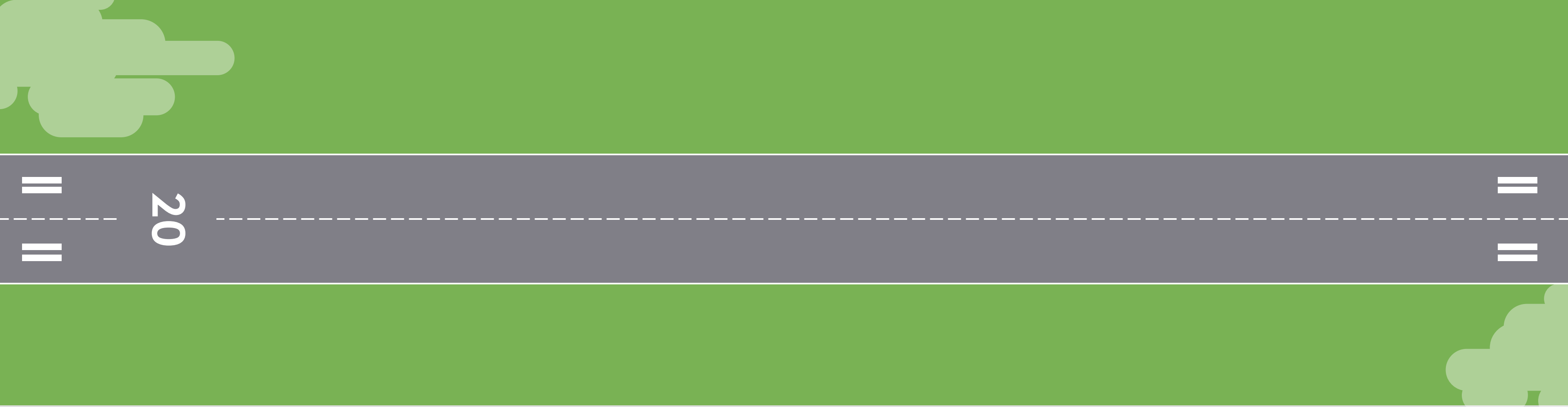
FAA AC-150/5060 5

The Cost of Overloading the Taxi Queue



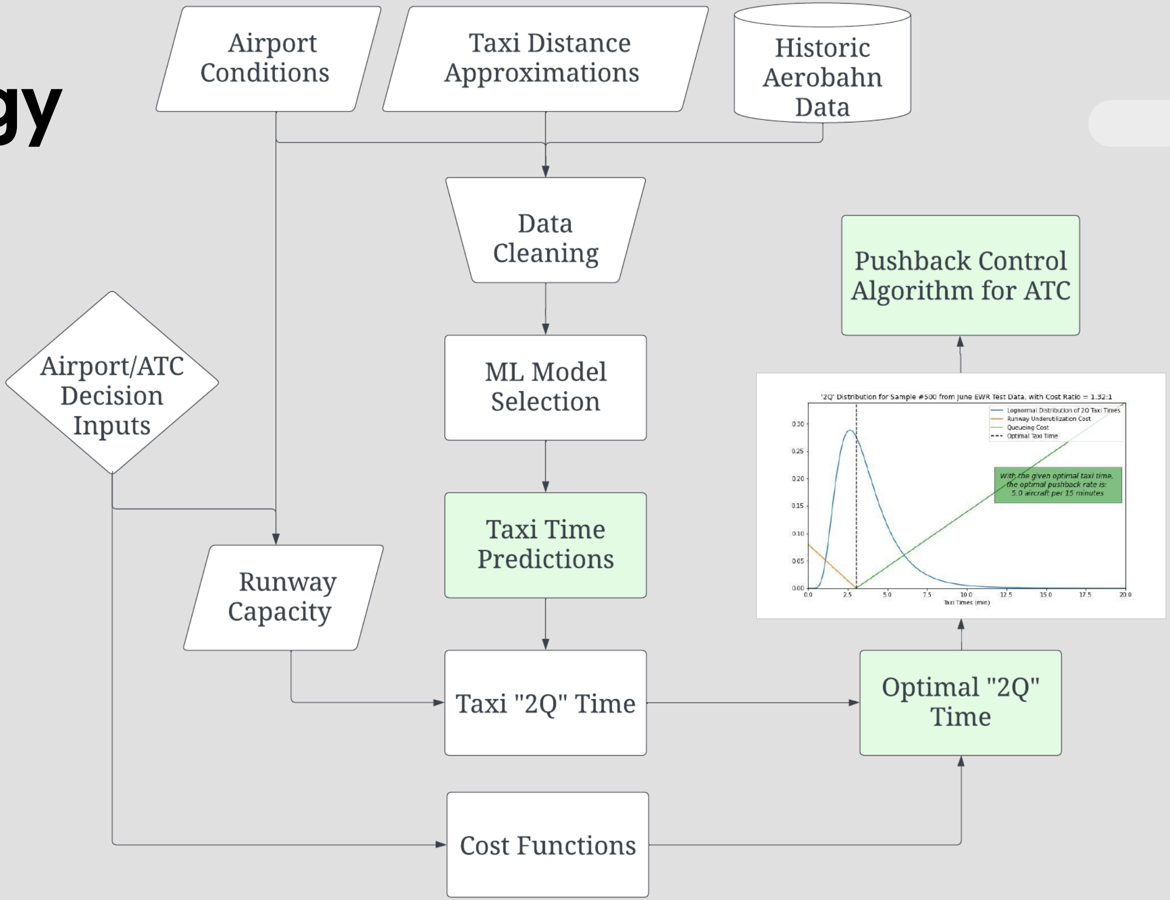
In 2022, airlines spent >30% of their operating budget on fuel, or $222 billion

Based on the size of the aircraft, it consumes anywhere between 12-42 gallons/min/engine



The goal of the present study, therefore, is to create a low fidelity, easily interpretable machine learning model to predict taxi times across airfield geometries and use this to feed into a taxi time optimization algorithm.

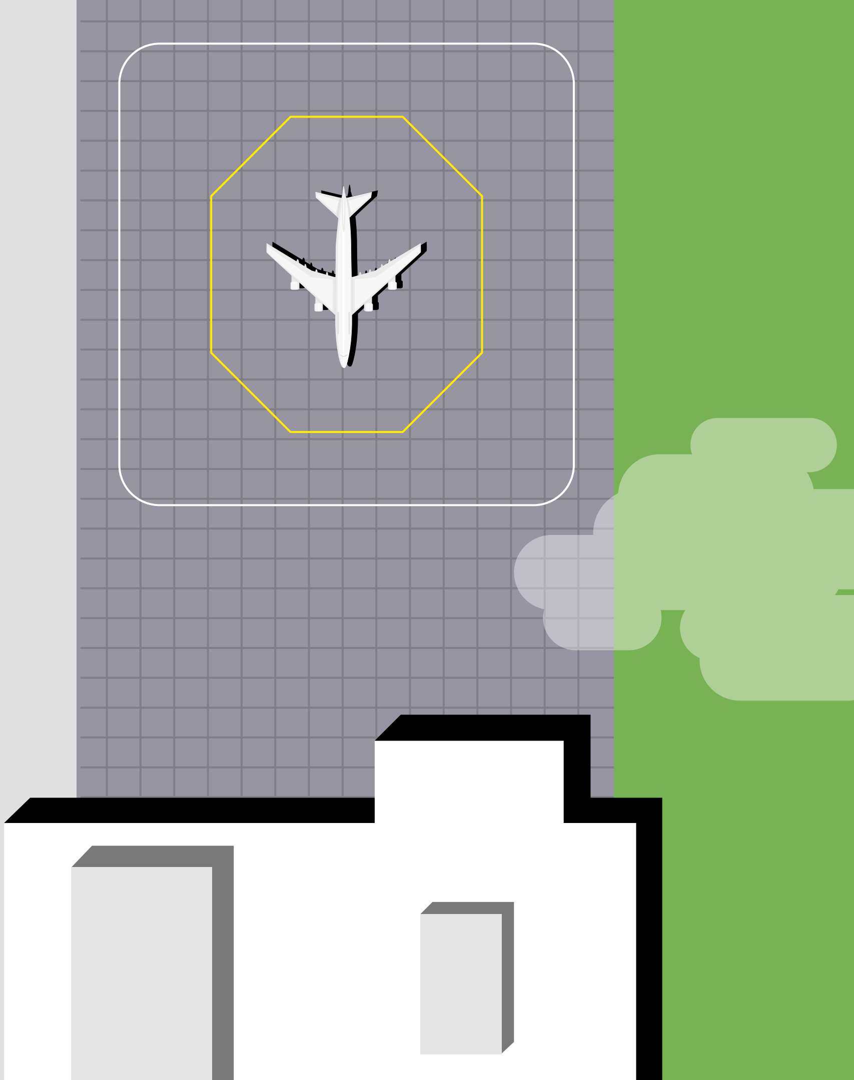
Methodology

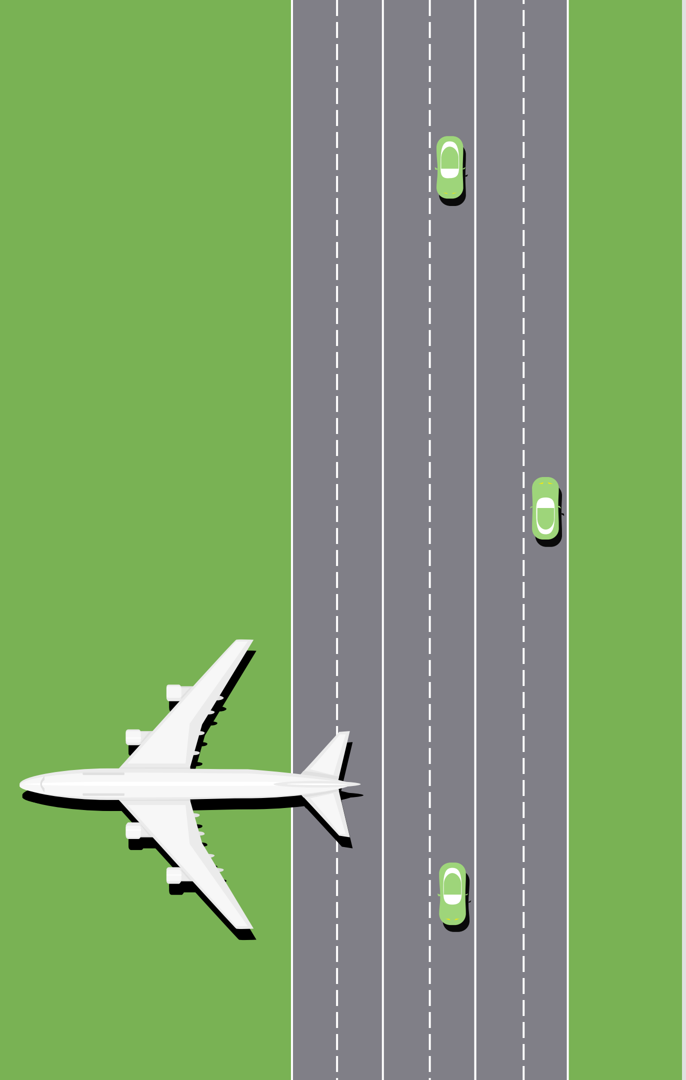


02

Target Variable

Where can we obtain historical taxi time data?





Industry Partnership

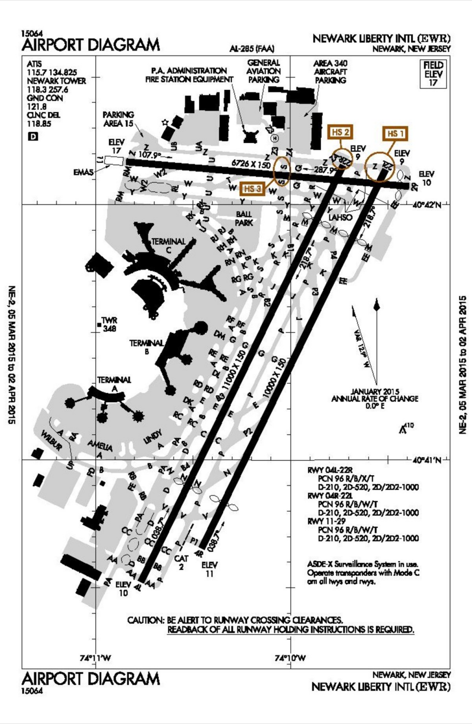
HNTB

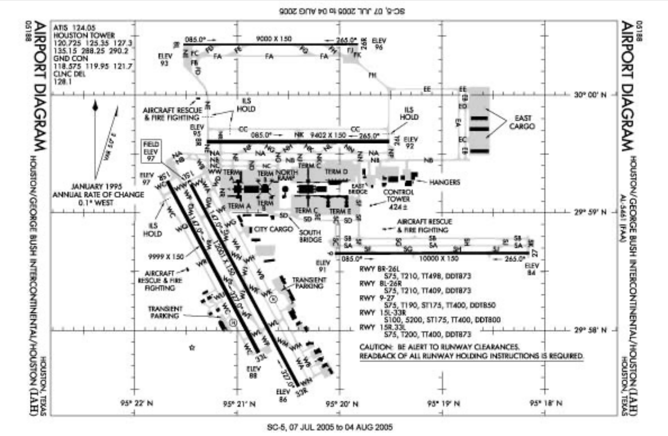
HNTB's Aviation Planning + Environmental Team and airport planners at each airport volunteered Aerobahn data with unmarked callsigns for:

- George Bush Intercontinental Airport (IAH)
- Newark International Airport (EWR)

This Aerobahn data included operation type, time, gate, and OOOI data: block **off**, wheels **off**, wheels **on**, and block **in** times.

Taxi Times at the Two Study Airports



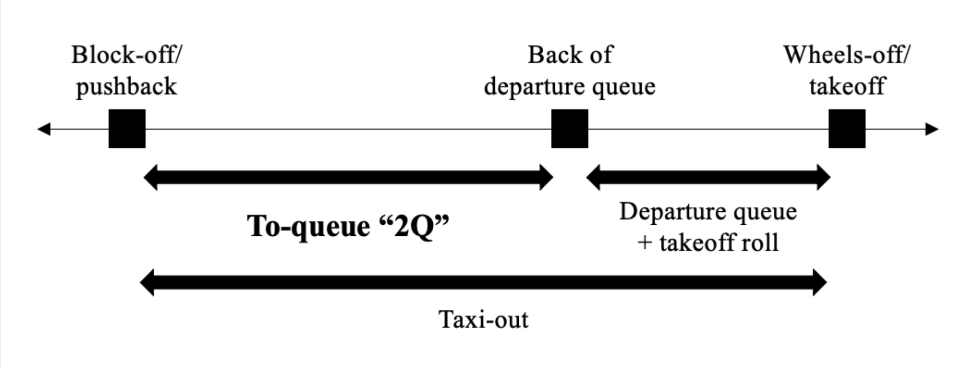


From the OOOI data, taxi times were calculated as:

Block In - Wheels On = Taxi-In Time
Wheels Off – Block Off = Taxi-Out Time

Dataset	July-Sept 2022 IAH	June 2022 IAH	June 2022 EWR
Average (in min)	17.96	17.39	21.31
Standard Deviation (in min)	4.80	4.04	7.11
Sample Size	*n* = 42,385	*n* = 14,073	*n* = 9,937

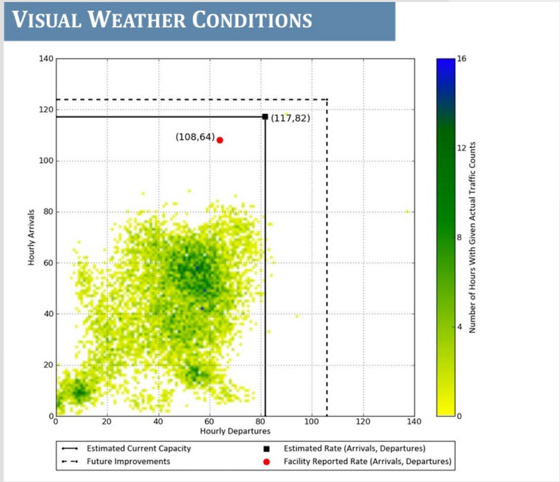
“2Q” Taxi Time



The departure taxi-out can be segmented into the queuing process and the unimpeded ”2Q” time from gate pushback to entering the back of the departure queue

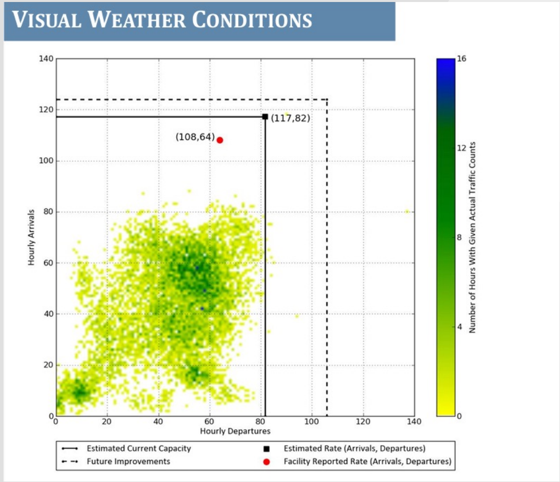
By predicting both the total taxi time and the 2Q time, the model performance can indicate how well the predictor variables capture variability in each of the two durations

2Q Derivation



$$\textit{Hourly Departure Throughput} \approx f(\textit{Airport, Meteorological Conditions, and Operation Focus})$$

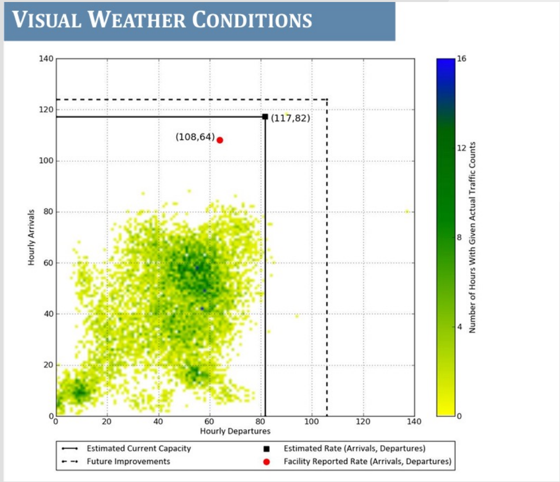
2Q Derivation



$$\textit{Hourly Departure Throughput} \approx f(\textit{Airport, Meteorological Conditions, and Operation Focus})$$

$$\textit{Runway Processing Time (in minutes)} \approx max\left[0, \left(nDepOut * \left(\frac{60 * \textit{Number of Departure Runways}}{\textit{Hourly Departure Throughput}}\right) - \frac{\textit{Taxi Distance}}{1519}\right)\right]$$

2Q Derivation



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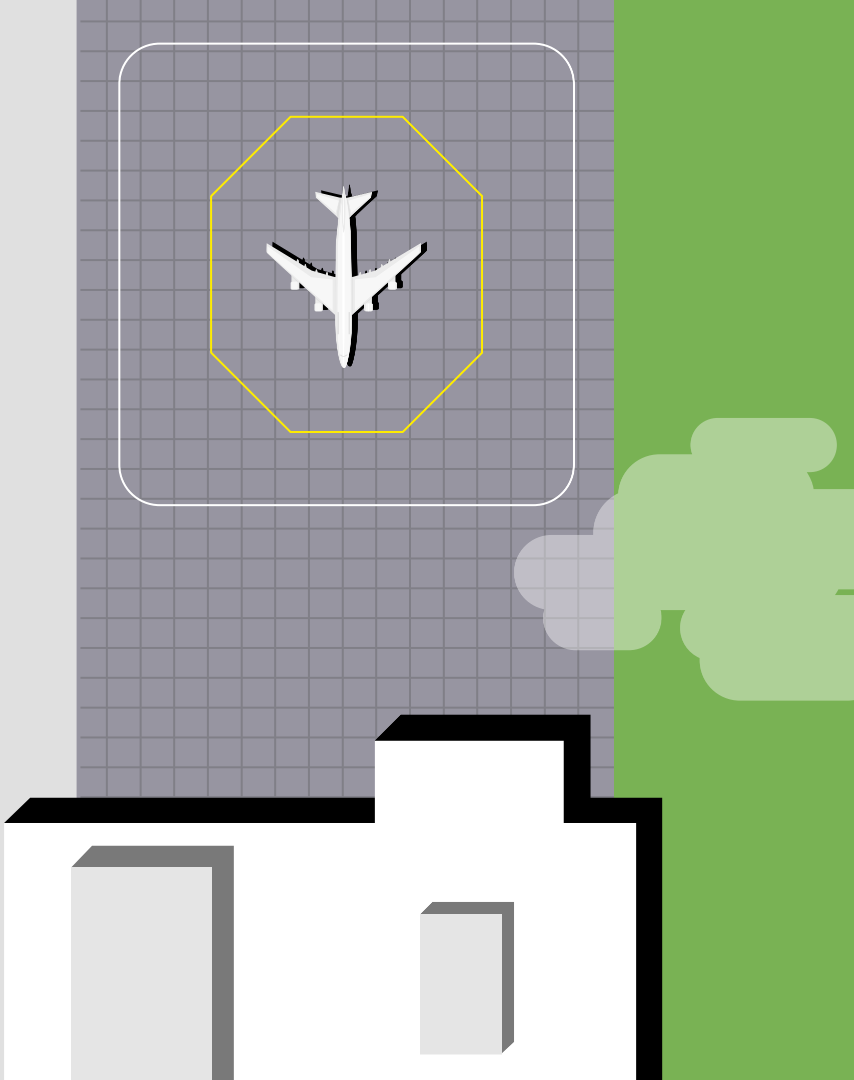
$$\boxed{\textit{2Q Time} \approx \textit{Taxi–Out Time} - \textit{Runway Processing Time}}$$

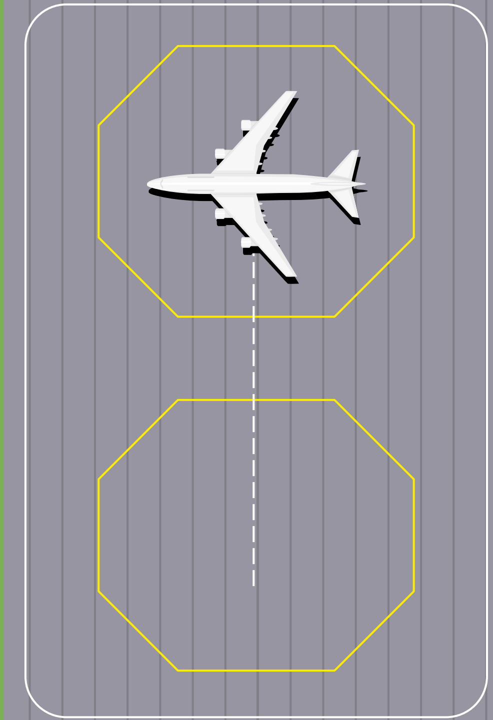
03

Predictor Variables

What data can explain the taxi time of an aircraft?



Calculating the Significant Features



Departure indicator

1 if aircraft operation is a departure; 0 if arrival

Distance

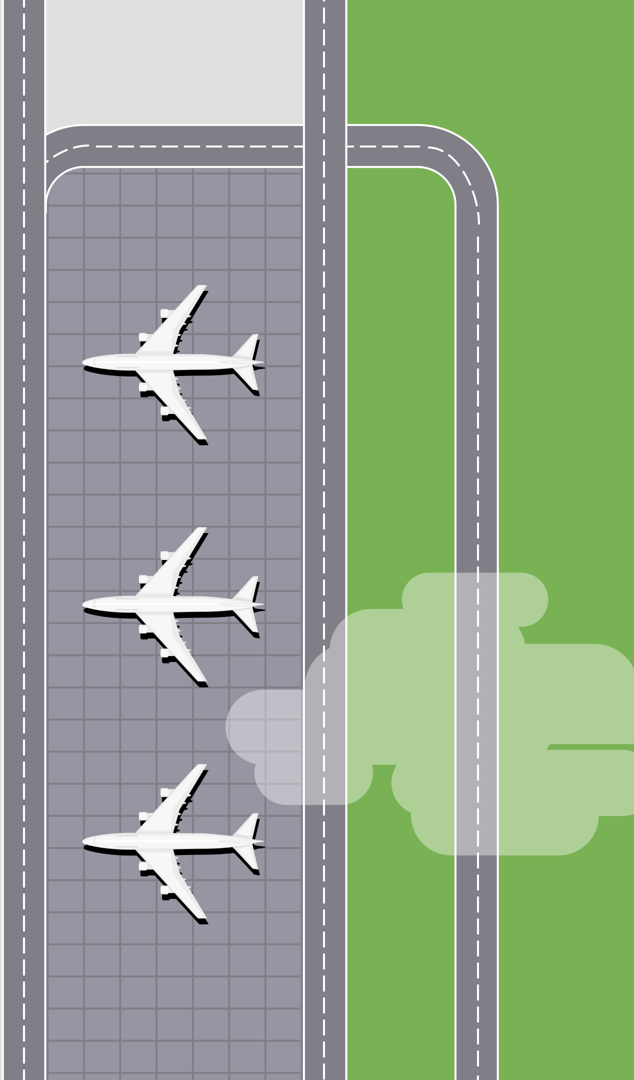
Traced minimum viable taxi pathway from gate concourse to runway threshold

nDepOut

Count of taxiing out aircraft who have pushed back but not yet taken off by the time of pushback for the study aircraft

Additional Features

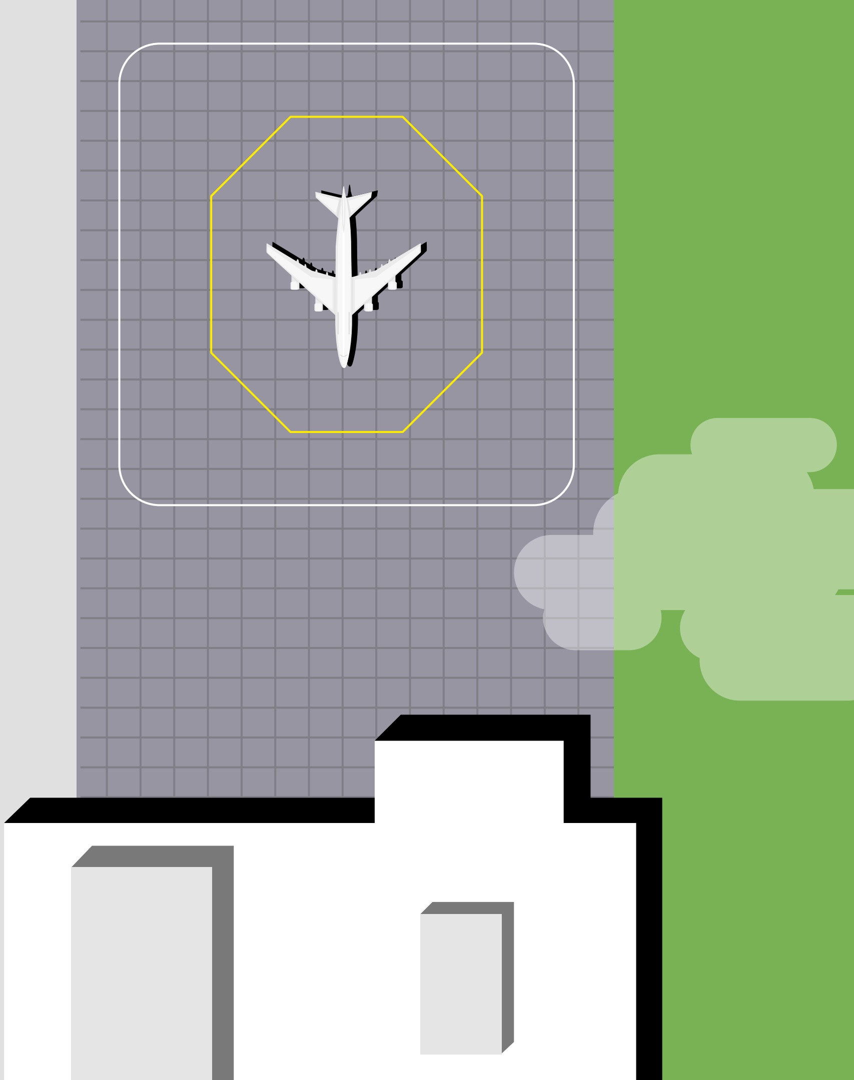
Feature	Unit	Description
Angle Sum	Degrees	Sum of angles turned through along the taxi pathway
nDepIn	# of aircraft	Number of aircraft taxiing to gate at time of pushback
nArrOut	# of aircraft	Number of aircraft taxiing to runway or in takeoff queue at time of landing
nArrIn	# of aircraft	Number of aircraft taxiing to gate at time of landing
Temperature	Degrees Fahrenheit	Surface temperature at the METAR data collection point
Wind Speed	Miles per hour	Wind speed at the METAR data collection point
Visibility	Statute miles	Visibility at the METAR data collection point



04

Regression

How well do the predictor variables allow us to forecast future performance?



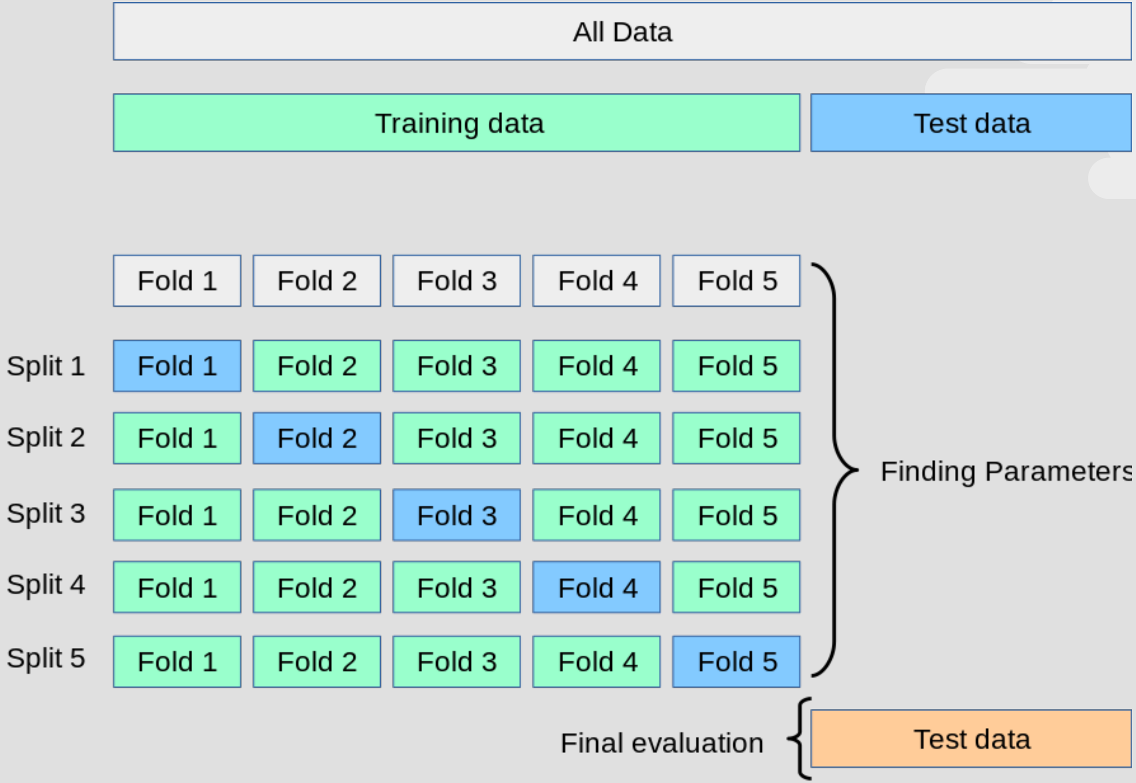
Preprocessing

$$x_{scaled} = \frac{x - x_{min}}{x_{max} - x_{min}}$$

$$y = \log(y)$$

Data scaling

Cross-Validation



Sci-kit Learn documentation

Original & 2Q Training Data Performance

Estimator	Total Taxi Time			2Q Taxi Time		
	Tuned Hyperparameters	R^2	RMSE	Tuned Hyperparameters	R^2	RMSE
Linear Regressor	N/A	0.45	0.40	N/A	0.64	0.67
Elastic Net Regressor	alpha = 0.1, l1_ratio = 0.01	0.39	0.43	alpha = 0.1, l1_ratio = 0.99	0.38	0.87
K-Neighbors Regressor	n_neighbors = 31	0.54	0.37	n_neighbors = 21	0.79	0.50
Decision Tree Regressor	max_depth = 9, max_leaf_nodes = 40	0.58	0.35	max_depth = 7, max_leaf_nodes = 40, min_samples_split = 62	**0.82**	**0.47**
Random Forest Regressor	max_depth = 10, max_leaf_nodes = 102, min_samples_split = 50	**0.61**	**0.34**	max_depth = 10, max_leaf_nodes = 102, min_samples_split = 50	**0.83**	**0.46**
Shallow Decision Tree Regressor	max_depth = 5, max_leaf_nodes = 20	0.54	0.37	max_depth = 5, max_leaf_nodes = 40	**0.82**	**0.47**
Shallow Random Forest Regressor	max_depth = 5, max_leaf_nodes = 102, min_samples_split = 50	0.55	0.37	max_depth = 5, max_leaf_nodes = 102, min_samples_split = 50	**0.82**	**0.47**

2Q Taxi Time Prediction Performance Results

Estimator	IAH – June 2022		EWR – June 2022	
	R^2	RMSE	R^2	RMSE
Linear Regressor	0.56	0.74	0.20	0.94
Elastic Net Regressor	0.40	0.92	-0.09	1.10
K-Neighbors Regressor	0.69	0.62	**0.22**	**0.93**
Decision Tree Regressor	**0.74**	**0.57**	0.16	0.97
Random Forest Regressor	**0.75**	**0.55**	0.18	0.95
Shallow Decision Tree Regressor	**0.74**	**0.57**	0.15	0.98
Shallow Random Forest Regressor	**0.76**	**0.54**	0.18	0.96

Simple Linear Regression

For the July - September 2022 IAH training dataset:

Estimator	Total Taxi Time			2Q Taxi Time		
	Tuned Hyperparameters	R^2	RMSE	Tuned Hyperparameters	R^2	RMSE
Linear Regressor	N/A	0.45	0.40	N/A	0.64	0.67

Linear Regressor on Total Taxi Time Data					
Departure_Indicator	Distance	Angle Sum	nArrOut	nArrIn	Intercept
0.74	0.47	-0.07	-0.05	0.51	
nDepOut	nDepIn	Temperature	Wind Speed	**Visibility**	1.56
0.36	P>0.05	0.14	0.09	**-0.09**	

Simple Linear Regression

For the July - September 2022 IAH training dataset:

Estimator	Total Taxi Time			2Q Taxi Time		
	Tuned Hyperparameters	R^2	RMSE	Tuned Hyperparameters	R^2	RMSE
Linear Regressor	N/A	0.45	0.40	N/A	0.64	0.67

Linear Regressor on 2Q Taxi Time Data

Departure_Indicator	**Distance**	Angle Sum	nArrOut	nArrIn	Intercept
0	**1.79**	-0.16	-0.09	-0.24	
nDepOut	nDepIn	Temperature	Wind Speed	Visibility	2.38
-4.51	-0.20	-0.43	-0.10	-0.20	

Investigating the 2Q Decision Tree Regressor

For the July - September 2022 IAH training dataset:

Estimator	Total Taxi Time			2Q Taxi Time		
	Tuned Hyperparameters	R^2	RMSE	Tuned Hyperparameters	R^2	RMSE
Shallow Decision Tree Regressor	max_depth = 5, max_leaf_nodes = 20	0.54	0.37	max_depth = 5, max_leaf_nodes = 40	**0.82**	**0.47**

Investigating the 2Q Decision Tree Regressor

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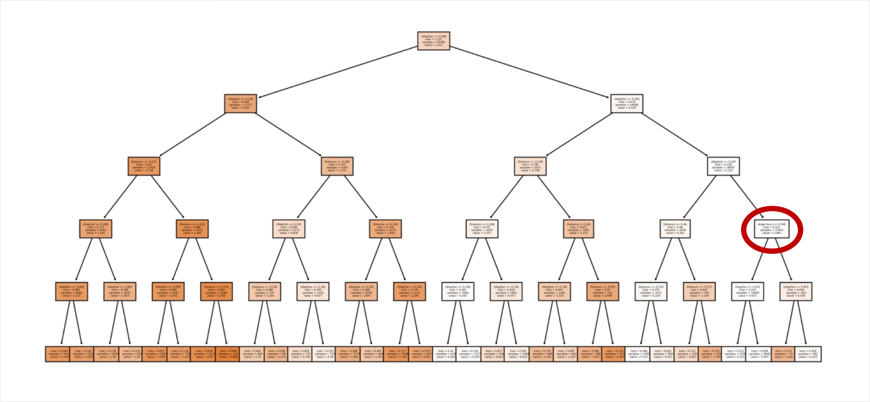

Depth: 5 levels

Total Branch Nodes: 31

Total Leaf Nodes: 32

Estimator	Total Taxi Time			2Q Taxi Time		
	Tuned Hyperparameters	R^2	RMSE	Tuned Hyperparameters	R^2	RMSE
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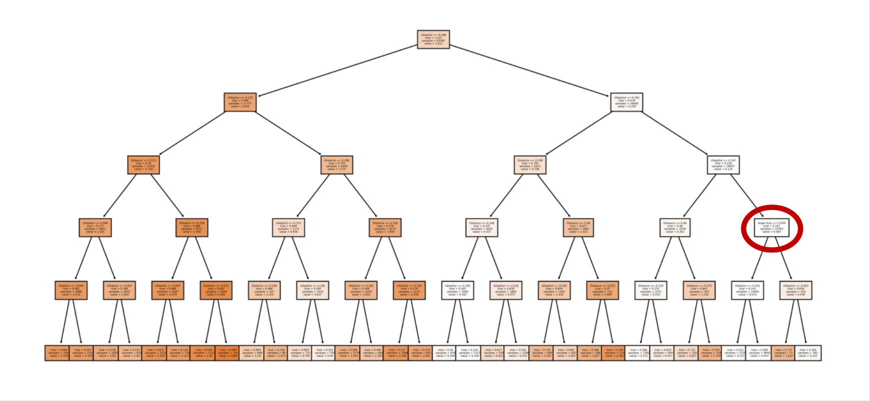

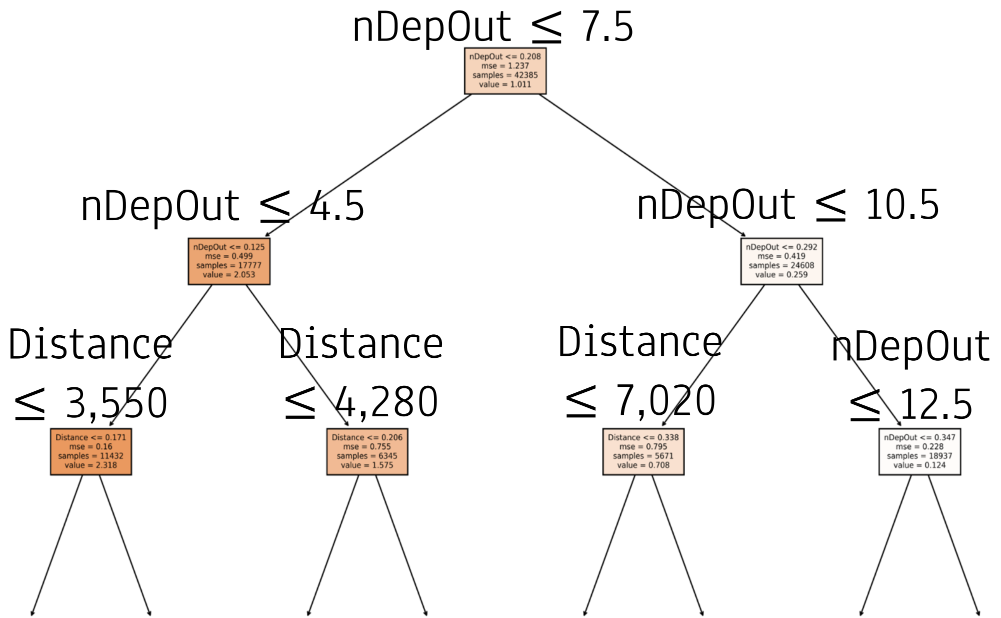

Depth: 5 levels
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Estimator	Total Taxi Time			2Q Taxi Time		
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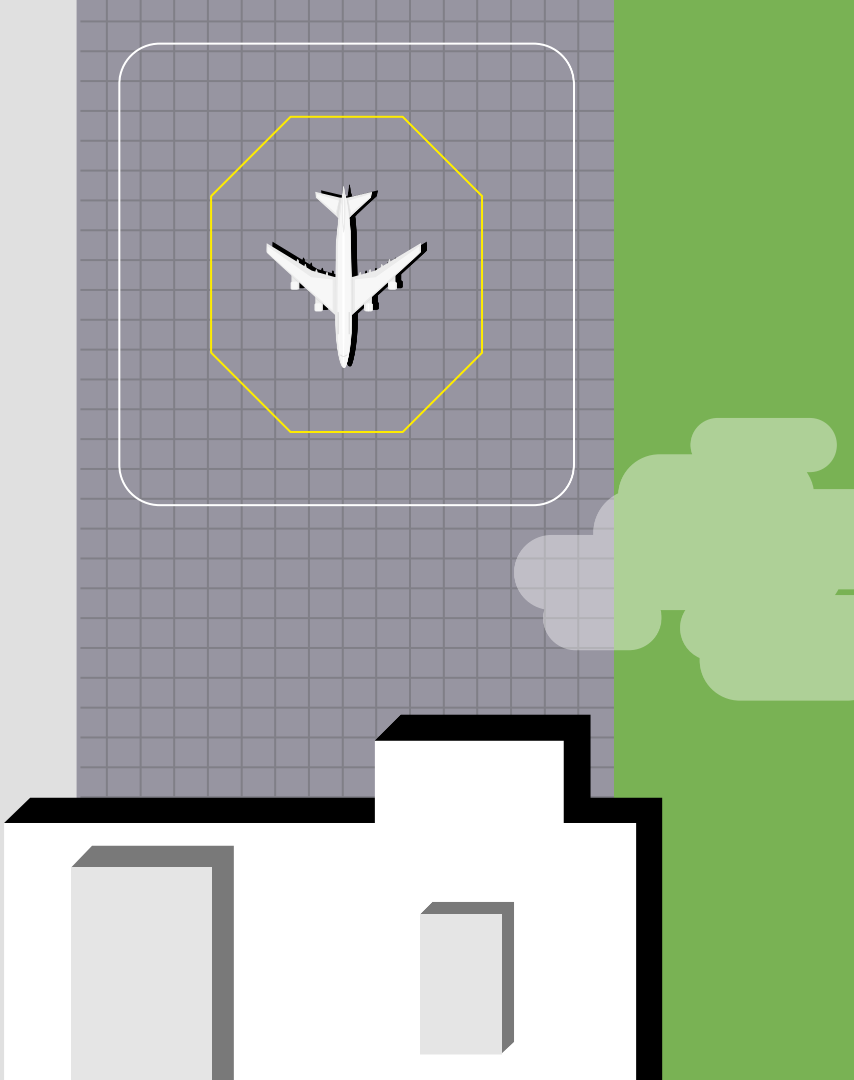
Shallow Decision Tree Regressor	max_depth = 5, max_leaf_nodes = 20	0.54	0.37	max_depth = 5, max_leaf_nodes = 40	**0.82**	**0.47**

05

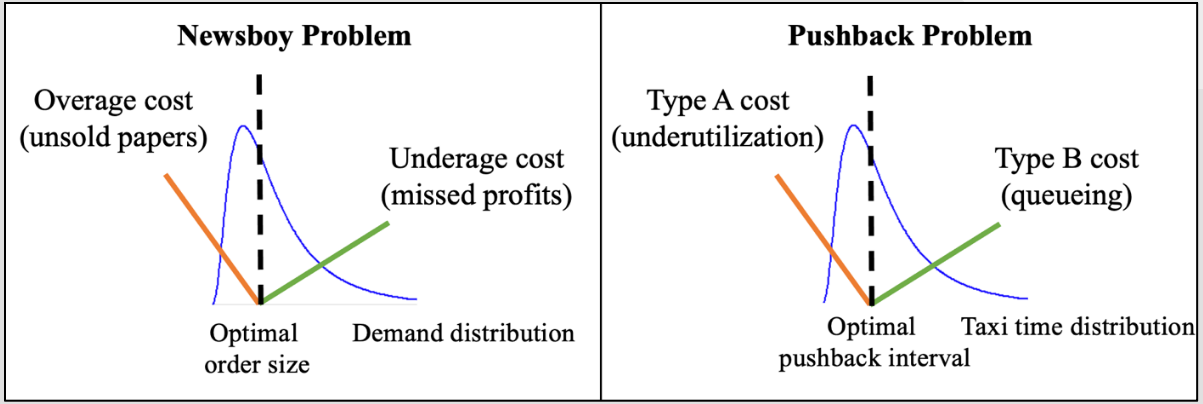
Optimization

How can we utilize the outputs from the ML model to make pushback decisions?



Optimization Formulation

The optimization is framed as a version of the operations research "newsboy problem":



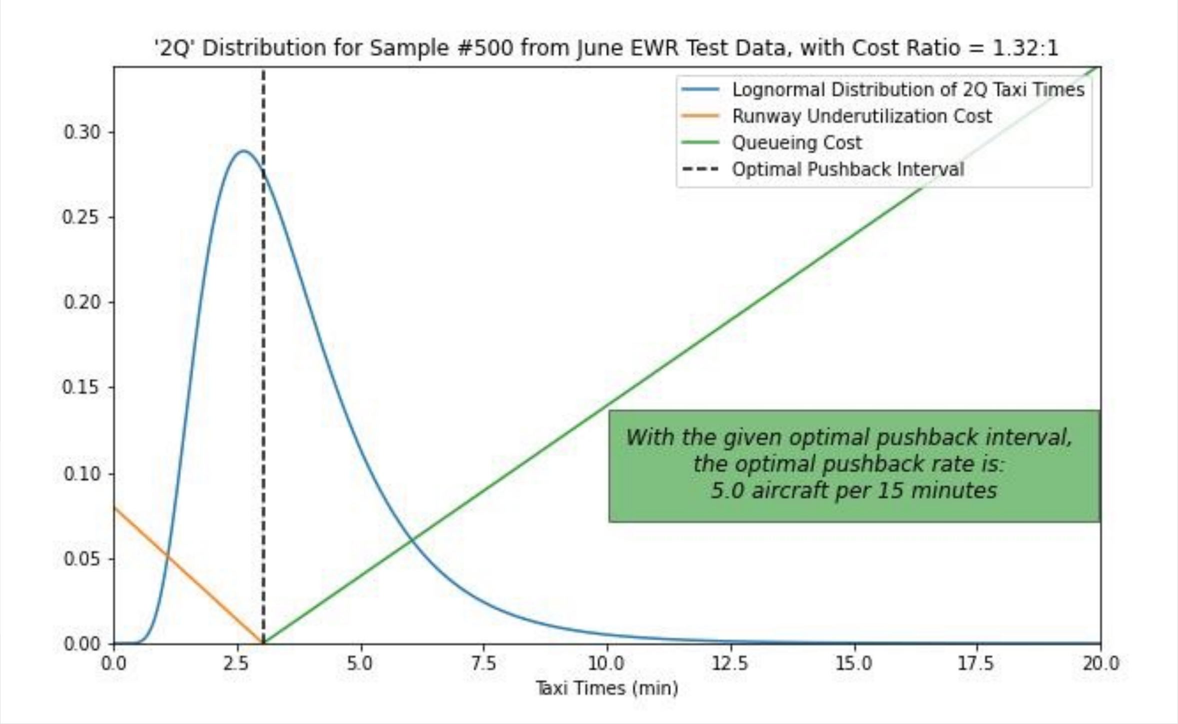
Given:

- An uncertain demand distribution
- A cost of purchasing papers
- A cost of missing out on sales (running out)

One can identify an optimal amount of papers to purchase by minimizing the integral of the area bounded by the x-axis and the product of the cost functions and demand distribution

$$Optimal\ Pushback\ Interval\ = F^{-1}\left(\frac{Type\ B\ Cost}{Type\ B\ Cost + Type\ A\ Cost}, \mu, \sigma\right)$$

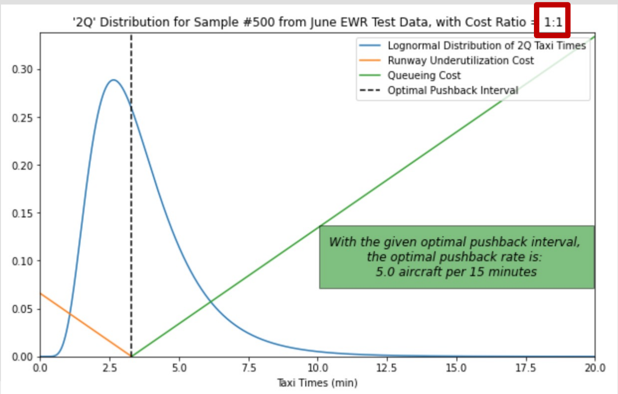
Optimization Output

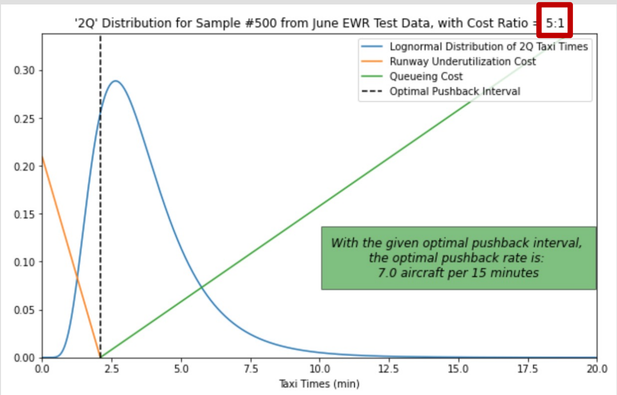


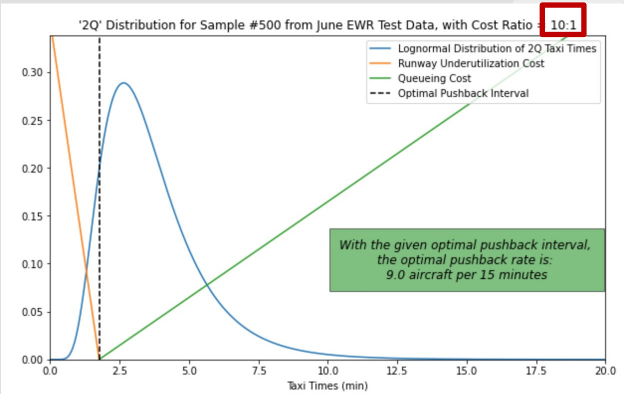
The optimization rests on two main pieces:

- The 2Q distribution
  - **Scale = ML model prediction**
  - **Standard deviation = RMSE of the ML model**
- The cost functions
  - Runway underutilization is 1.32 times more expensive than the queuing cost based on our delay calculations
  - However, this ratio can be changed to match airports' preference

Optimization Sensitivity to Cost Function

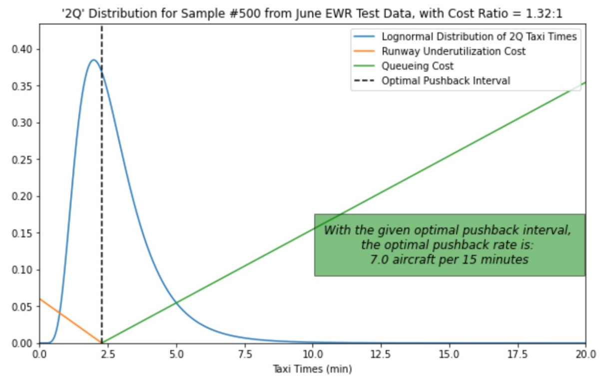


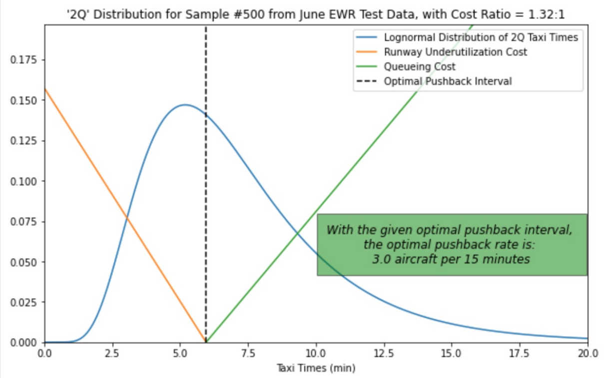


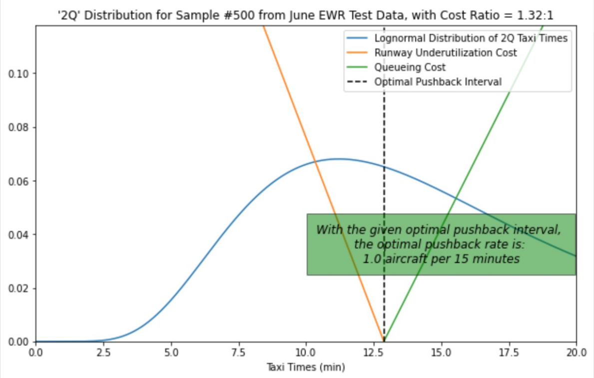


Under the same 2Q taxi time lognormal distribution, the optimal pushback interval <u>decreases</u> as the runway utilization to queuing cost ratio <u>increases</u>.

Optimization Sensitivity to Distribution





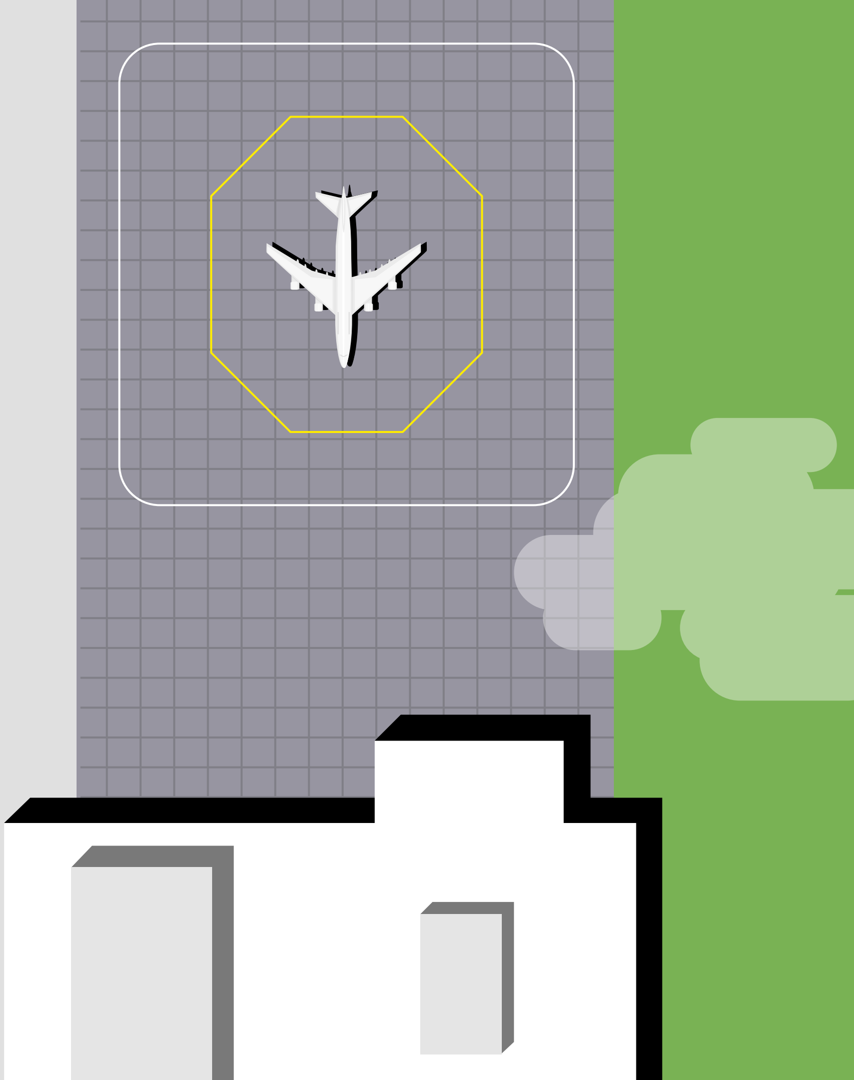


Under the same cost function ratio, the optimal pushback interval increases as the prediction of the 2Q taxi time—the scale of the lognormal distribution—increases.

06

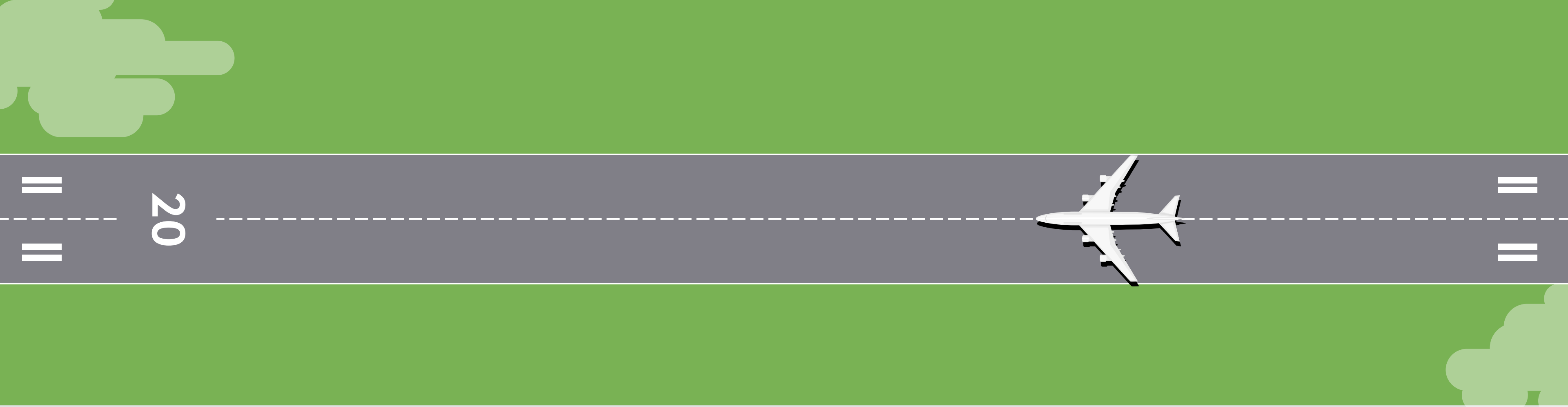
Discussion

What can be learned from this project, and how can future work build on what was studied?



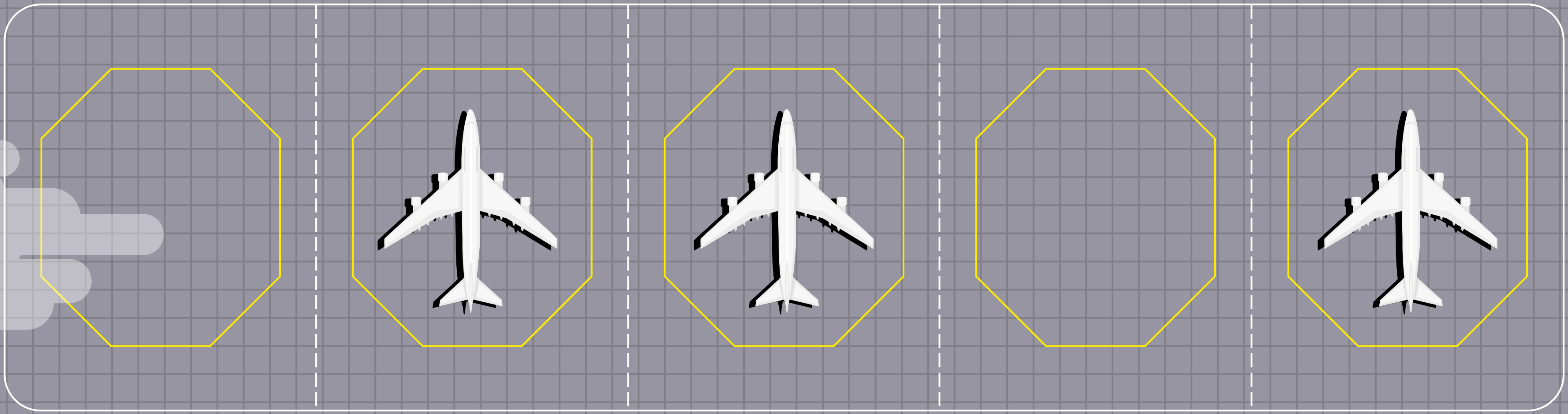
Limitations

- Small data sample size
    - Ideally, the model would be trained on more than just three months of data and have more testing data at EWR than ≈ 5,000 departures
- At present, the optimization only is carried out for an individual aircraft, and *not tightly constrained*
    - 2Q taxi time prediction is subject to significant variation
- Capturing the ground truth



Future Work

- Create a proof-of-concept of the pushback control algorithm that results from the optimization formulation
  - Converting theoretical optimal 2Q taxi times into practice via ATC ground control presents a significant hurdle
- Evaluate this method via simulation versus other known pushback strategies like N-Control



Any Questions?

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