

Using Machine-Learning to Dynamically Generate Operationally Acceptable Strategic Reroute Options

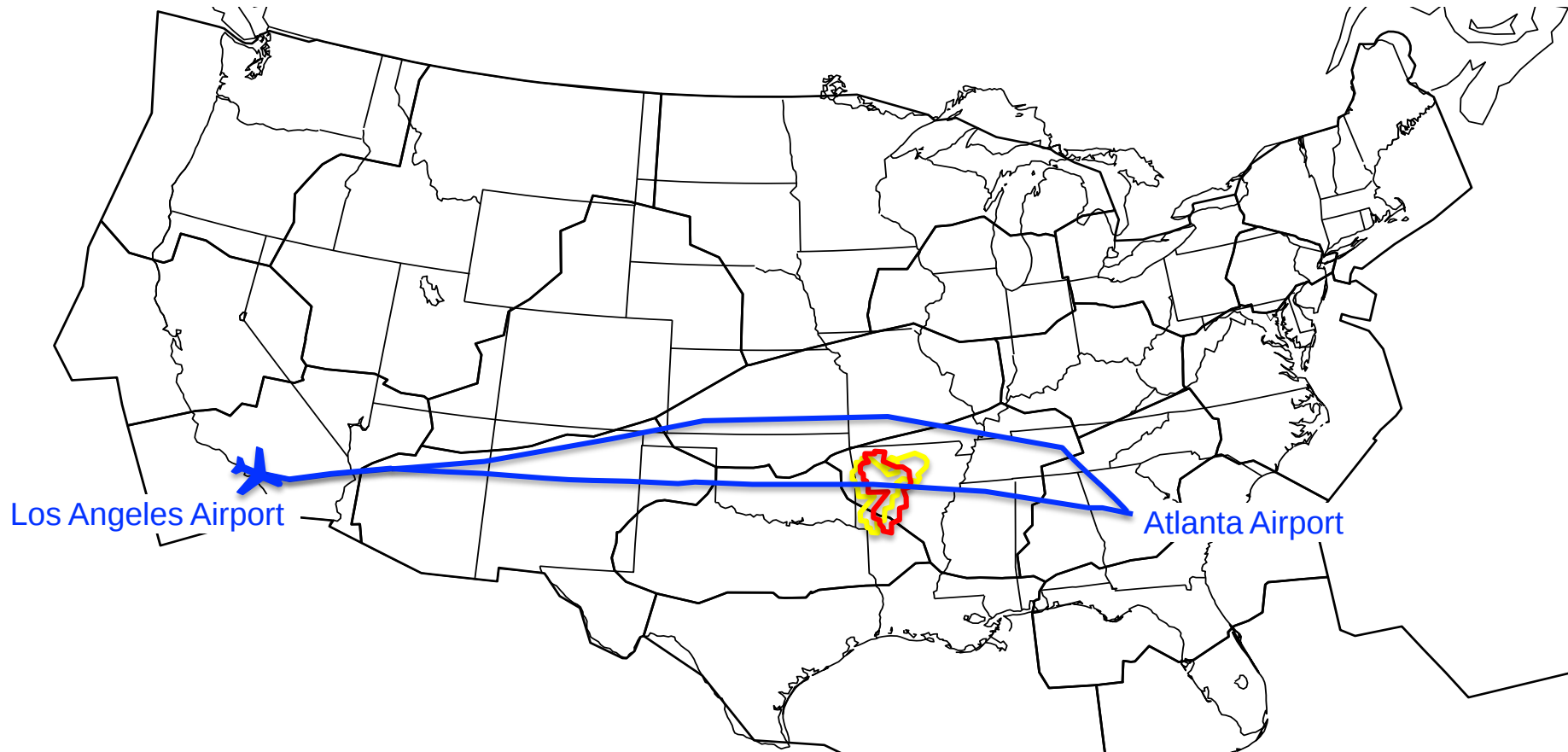
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Paul Lee (NASA Ames)

* Now working for Airbus

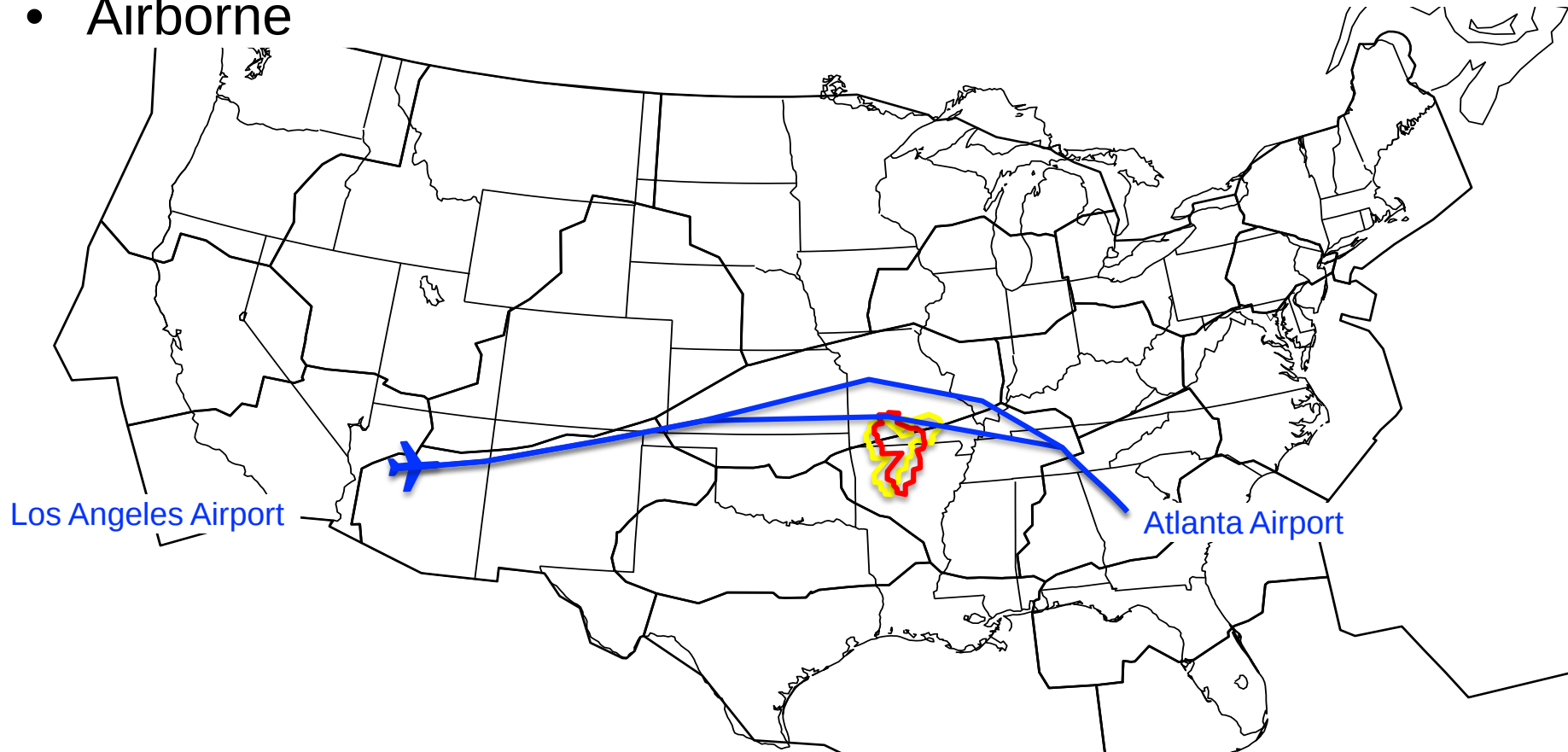
Strategic Rerouting

- Hours before departure
- Pre-departure



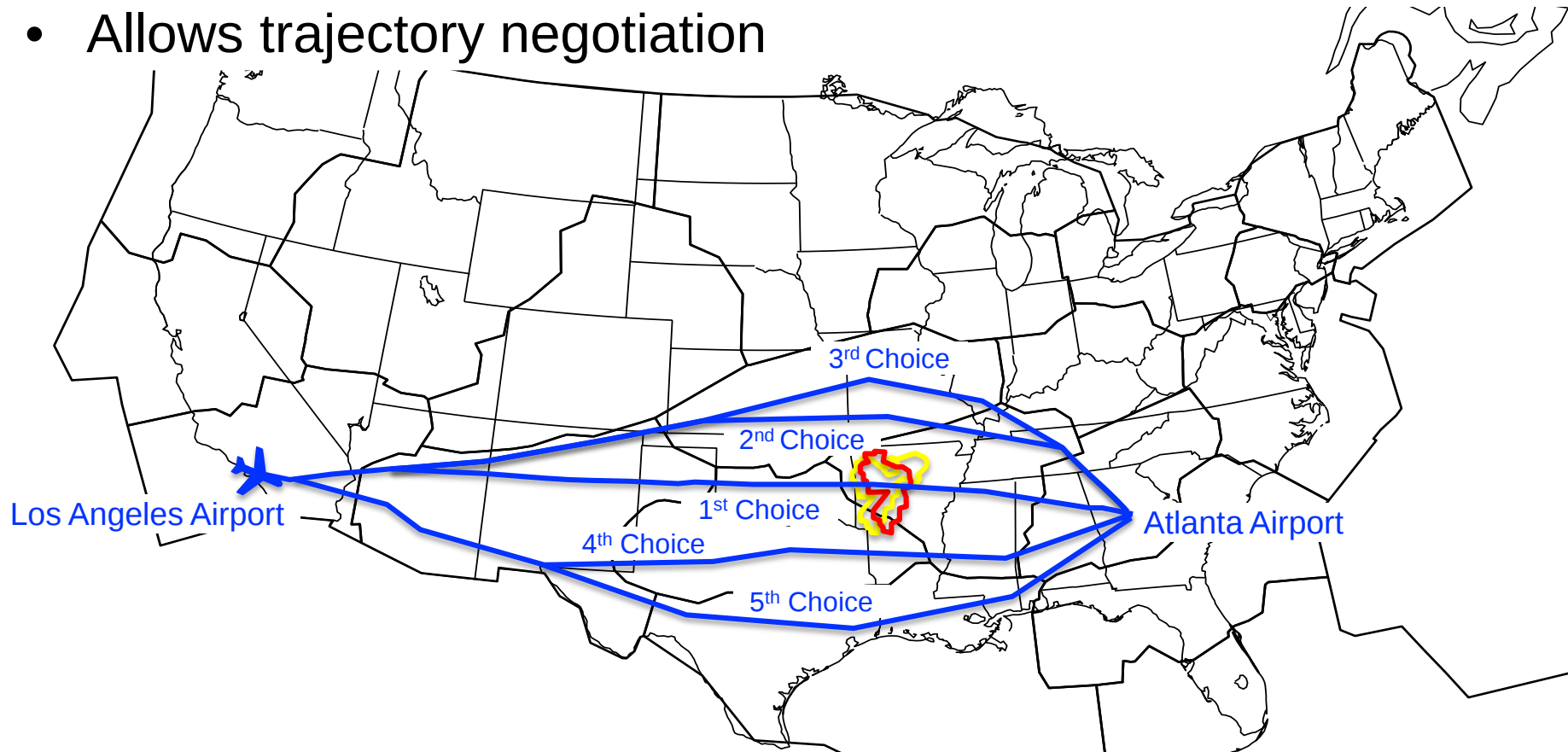
Strategic Rerouting

- Hours before departure
- Pre-departure
- Airborne



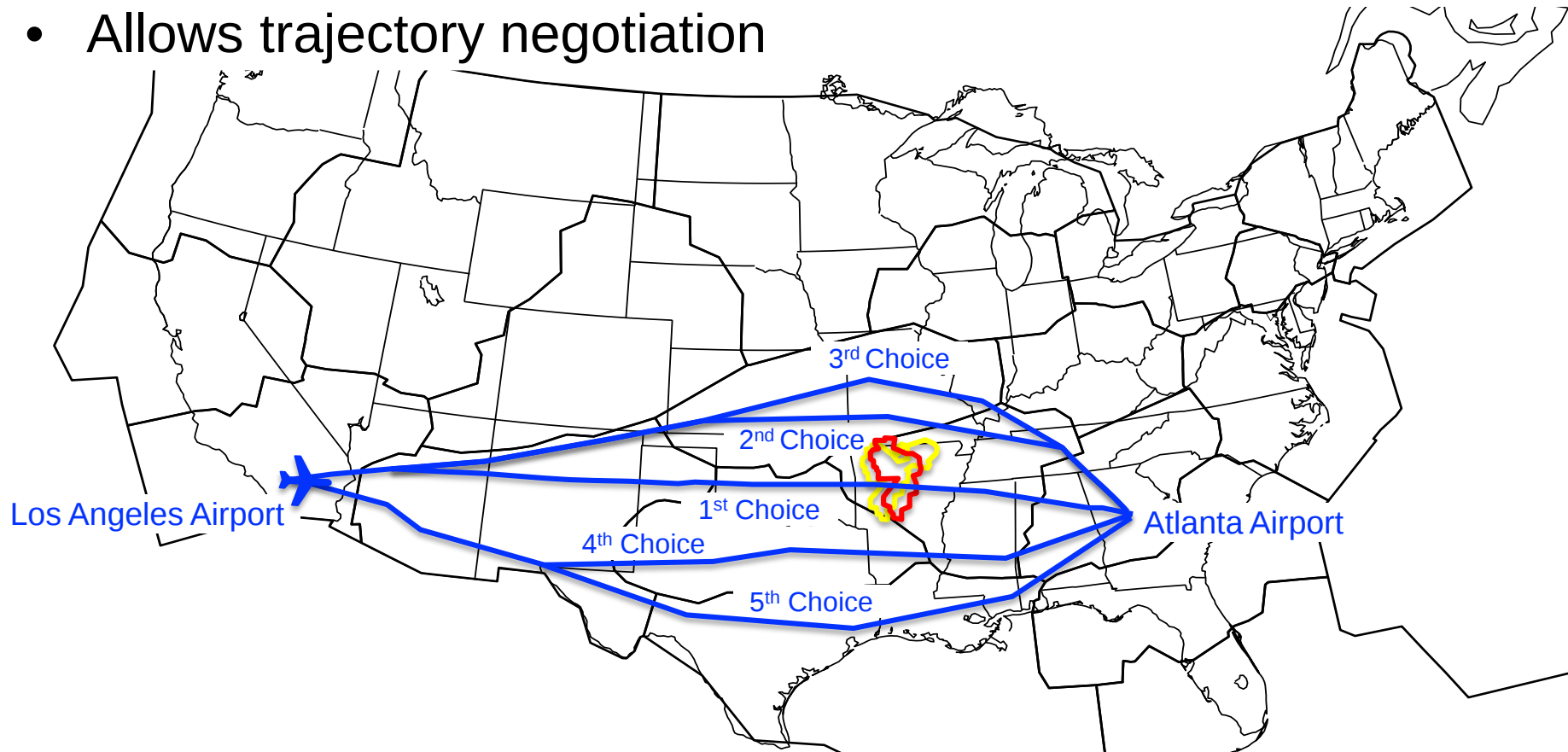
Trajectory Option Set (TOS)

- Preference-weighted set of alternative routes submitted by flight operators
- Allows trajectory negotiation



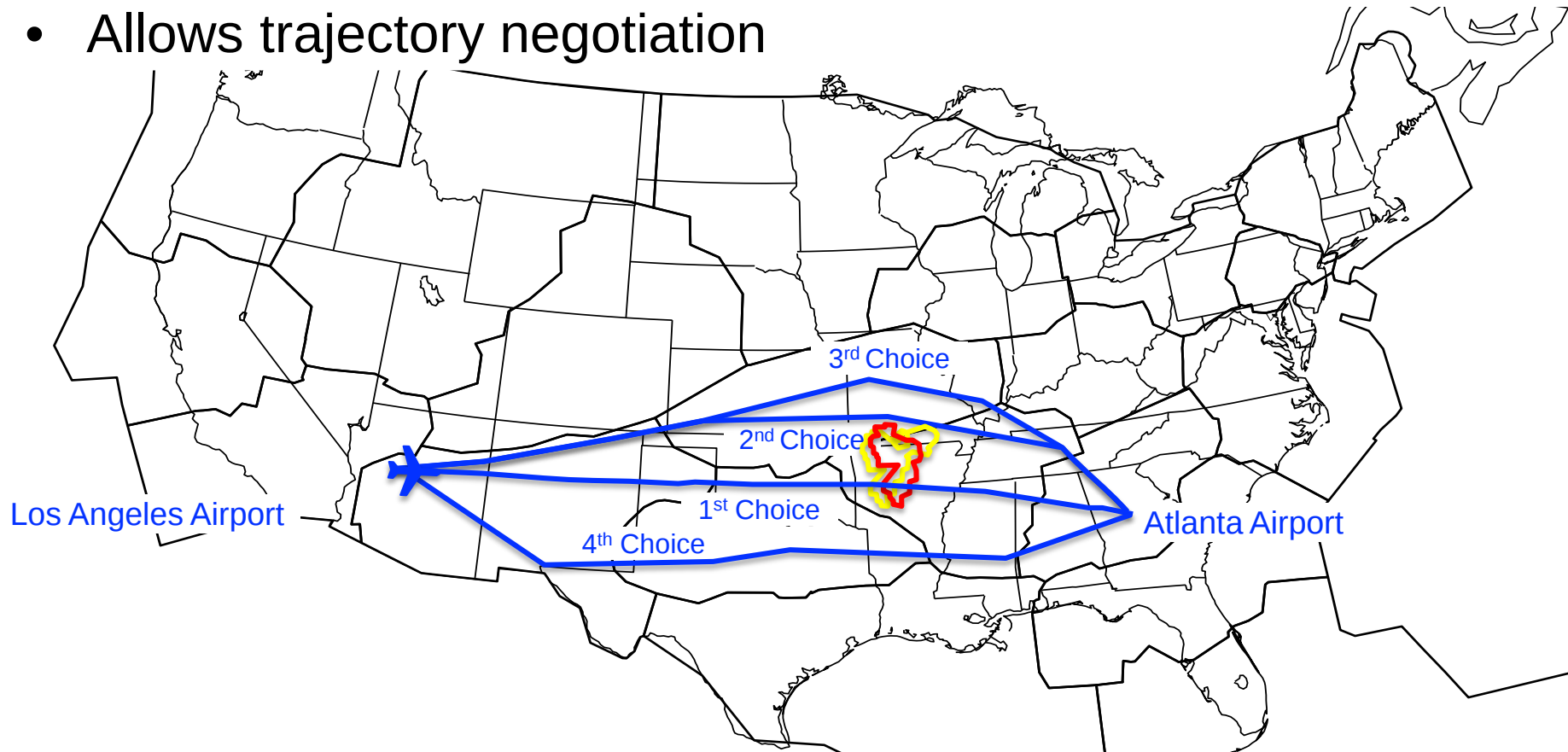
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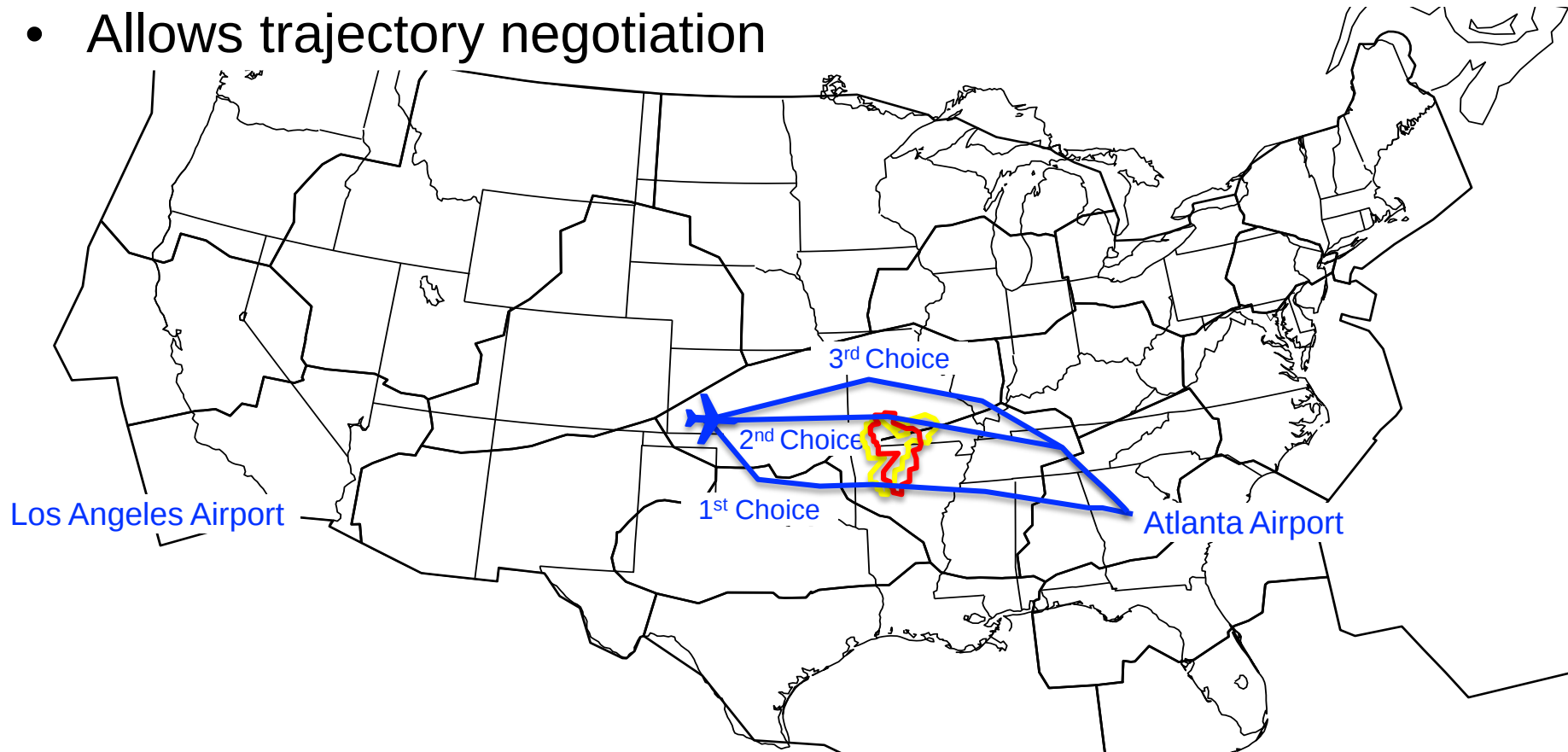
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Trajectory Negotiation

- Advantages
 - Enables flight operators to tailor trajectories based on preferences
 - Enables better utilization of available airspace resources
 - Reducing delay & increasing throughput
 - Increases predictability
- Barriers
 - Routes must be operationally acceptable

Can we automatically generate a TOS with high probability of operational acceptance?

Literature Review

Hall, W., Hunter, G., "Trajectory Optimization and the Clearable Route Network," 2018.

- Commercial TOS generators under development, accounting for historical usage

Idris H., *et al.*, "Assessment of Air Traffic Controller Acceptability of Aircrew Route Change Requests," 2017.

- Studies completed on operational acceptability

Taylor, C., Wanke, C., "Dynamically Generating Operationally Acceptable Route Alternatives Using Simulated Annealing," 2012.

- Models generating strategic routes using optimization, constrained to meet criteria that make it operationally acceptable

Evans, A.D., Lee, P., "Predicting the Operational Acceptance of Route Advisories," 2017.

- Previous NASA work uses machine learning to predict operational acceptability of airborne reroute requests

Objective

Automatically generate routes that have high probability of operational acceptance

Method: Use machine learning to train predictors on operational acceptance of strategic routes

Approach to TOS Generation

1. Identify available trajectory options • Based on historical routes



2. Down-select trajectory options

- Using route clustering
- Defines set of geographically distinct routes



3. Predict operational acceptability

- Using machine learning algorithms
- Given static and dynamic conditions



4. Select TOS

- Based on location of constraint and probability of trajectory acceptance by ATC

1. Identify Available Trajectory Options

Historical Usage

Flight Data

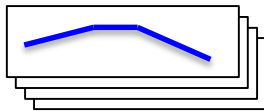
April
2015

May
2015

June
2015



Flight Plans, Flight Plan Amendments



Database of Trajectory Options

Flight ID	Alt	Alt	Alt	Alt
10000	10000	10000	10000	10000
10001	10001	10001	10001	10001
10002	10002	10002	10002	10002
10003	10003	10003	10003	10003
10004	10004	10004	10004	10004
10005	10005	10005	10005	10005
10006	10006	10006	10006	10006
10007	10007	10007	10007	10007
10008	10008	10008	10008	10008
10009	10009	10009	10009	10009
10010	10010	10010	10010	10010
10011	10011	10011	10011	10011
10012	10012	10012	10012	10012
10013	10013	10013	10013	10013
10014	10014	10014	10014	10014
10015	10015	10015	10015	10015
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10099	10099	10099	10099	10099
10100	10100	10100	10100	10100

1. Identify Available Trajectory Options

Historical Usage

Flight Data

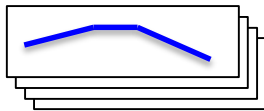
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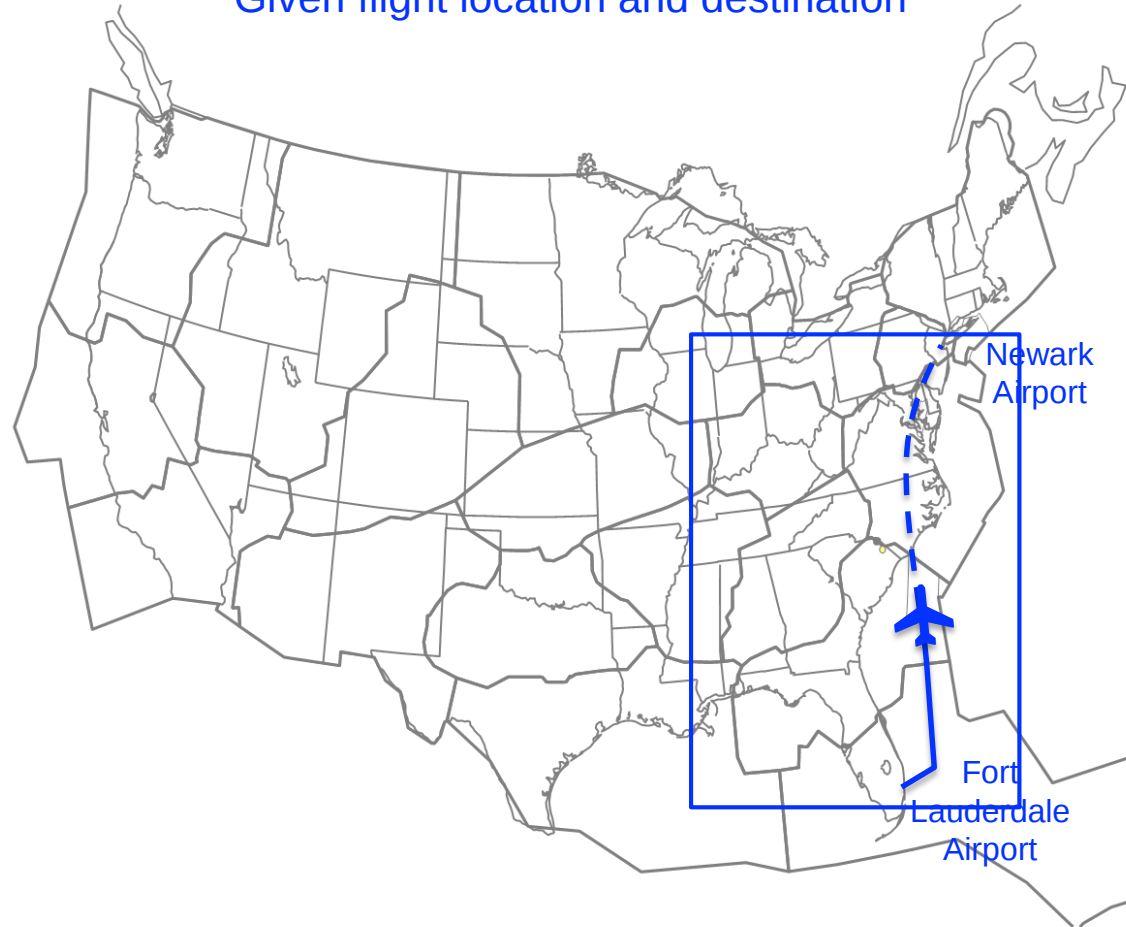
Flight Plans, Flight Plan Amendments



Database of Trajectory Options

[illegible]

Given flight location and destination



1. Identify Available Trajectory Options

Historical Usage

Flight Data

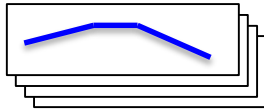
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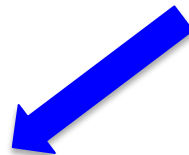


Flight Plans, Flight Plan Amendments

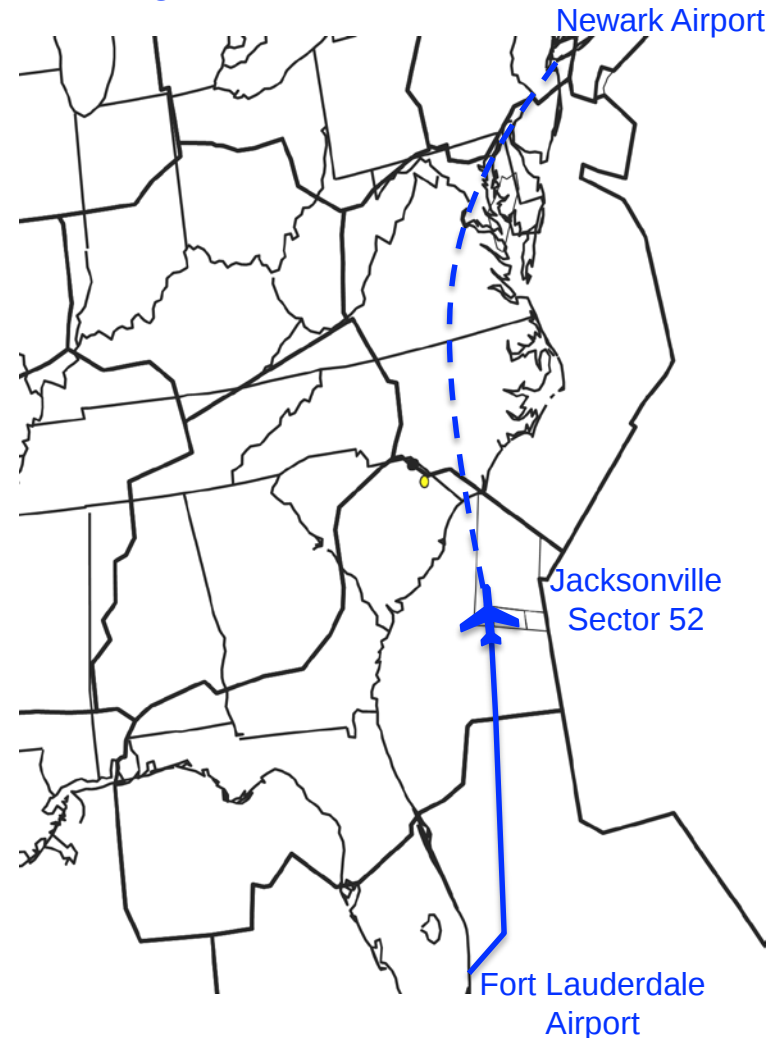


Database of Trajectory Options

Flight ID	Altitude	Speed	Heading	Altitude	Speed	Heading	Altitude	Speed	Heading
1001	10000	250	090	10000	250	090	10000	250	090
1002	10000	250	090	10000	250	090	10000	250	090
1003	10000	250	090	10000	250	090	10000	250	090
1004	10000	250	090	10000	250	090	10000	250	090
1005	10000	250	090	10000	250	090	10000	250	090
1006	10000	250	090	10000	250	090	10000	250	090
1007	10000	250	090	10000	250	090	10000	250	090
1008	10000	250	090	10000	250	090	10000	250	090
1009	10000	250	090	10000	250	090	10000	250	090
1010	10000	250	090	10000	250	090	10000	250	090



Given flight location and destination



1. Identify Available Trajectory Options

Historical Usage

Flight Data

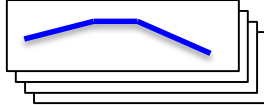
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Flight Plans, Flight Plan Amendments



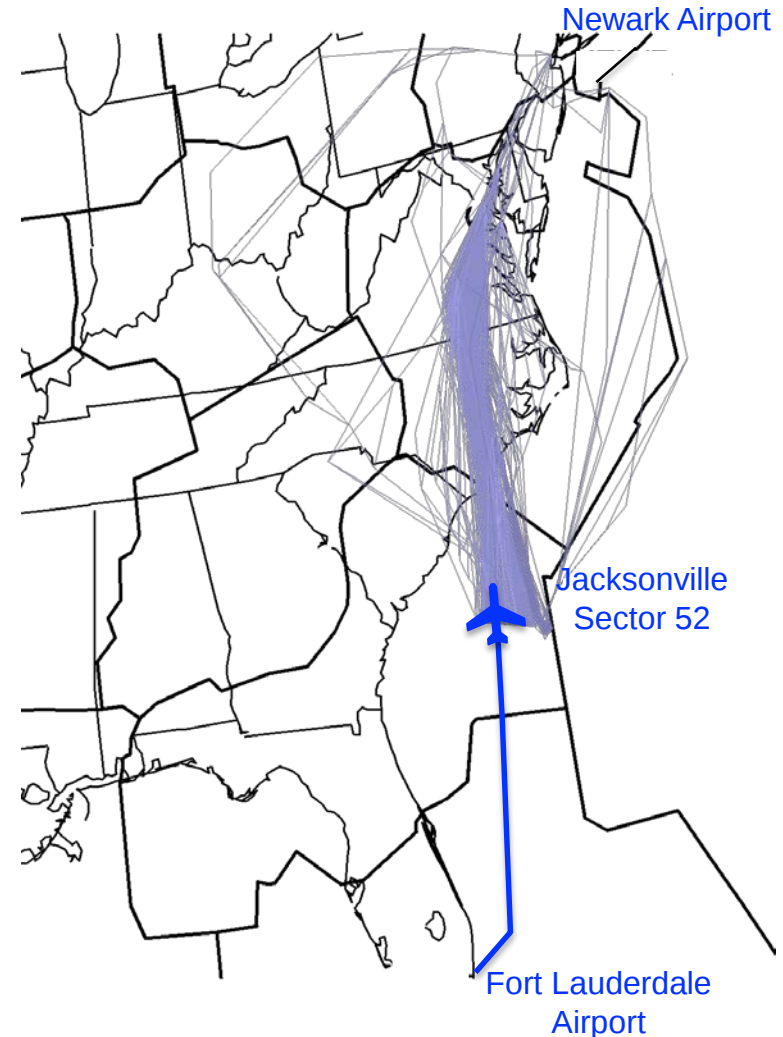
Database of Trajectory Options

Trajectory ID	Altitude	Time	Fuel	Cost
1	30000	120	10000	100
2	35000	110	9000	90
3	40000	100	8000	80
4	45000	90	7000	70
5	50000	80	6000	60
6	55000	70	5000	50
7	60000	60	4000	40
8	65000	50	3000	30
9	70000	40	2000	20
10	75000	30	1000	10



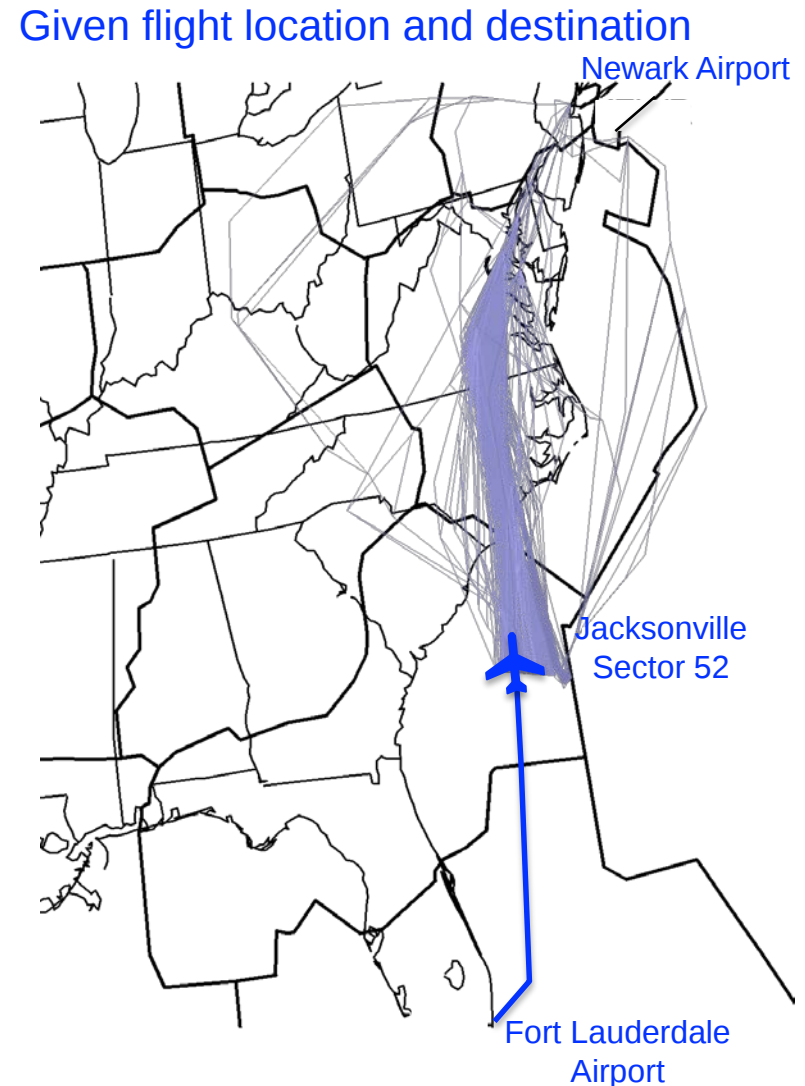
Historical Trajectories

Given flight location and destination



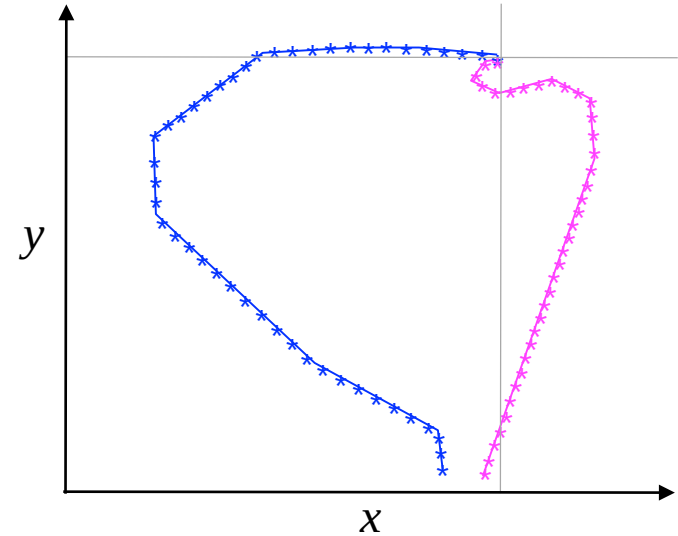
2. Down-Select Trajectory Options

- Apply Hierarchical clustering
- Dissimilarity metric calculated as Euclidean distance between trajectories
 - Each trajectory represented by a fixed length vector
 - Linear interpolation of 2D spatial position for 200 evenly spaced points



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$$tr_i = (x_{i1}, y_{i1}, x_{i2}, y_{i2}, \dots, x_{iN}, y_{iN})$$
$$tr_j = (x_{j1}, y_{j1}, x_{j2}, y_{j2}, \dots, x_{jN}, y_{jN})$$

...

$$d_{ij} = \sqrt{(x_{i1} - x_{j1})^2 + (y_{i1} - y_{j1})^2 + \dots + (x_{iN} - x_{jN})^2 + (y_{iN} - y_{jN})^2}$$

...

2. Down-Select Trajectory Options

- Apply Hierarchical clustering
- Dissimilarity metric calculated as Euclidean distance between trajectories
- Number of clusters identified based on maximizing avg. Silhouette score

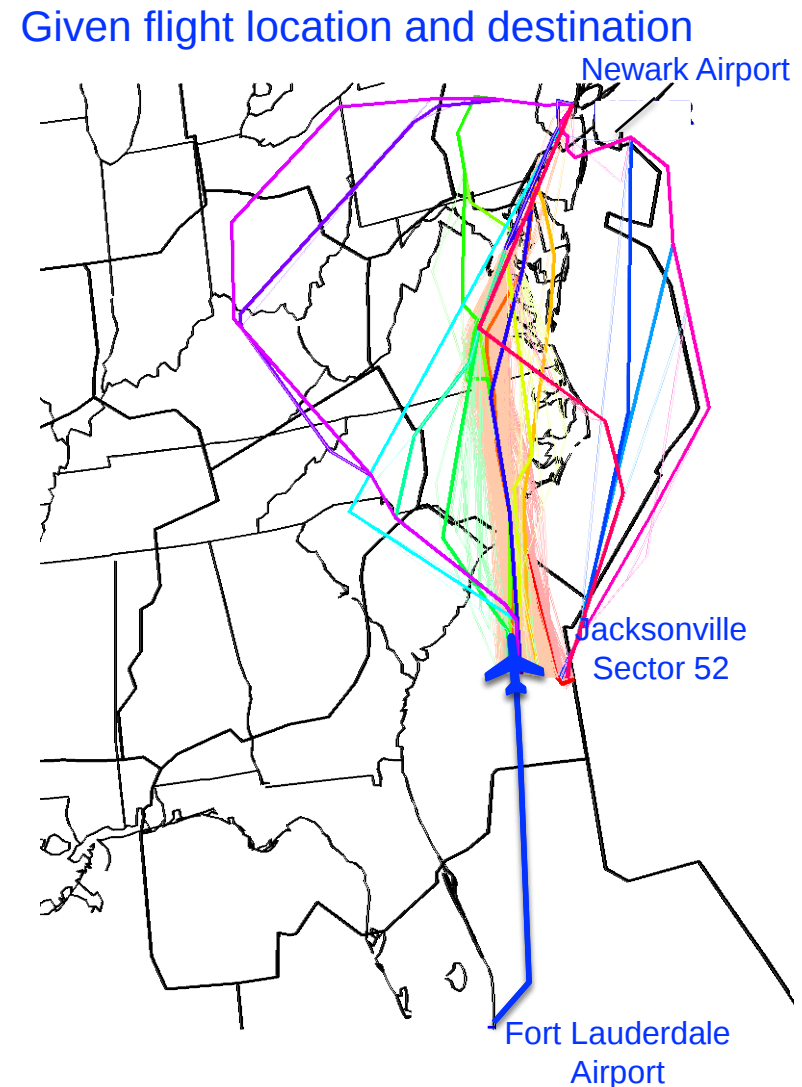
$$S = \frac{\min(\text{intercluster dist.}) - \text{intracluster dist.}}{\max(\min(\text{intercluster dist.}), \text{intracluster dist.})}$$

$$\bar{S} = \frac{1}{N_r} \sum_1^{N_r} S_i$$

- Minimum number of clusters set to 15

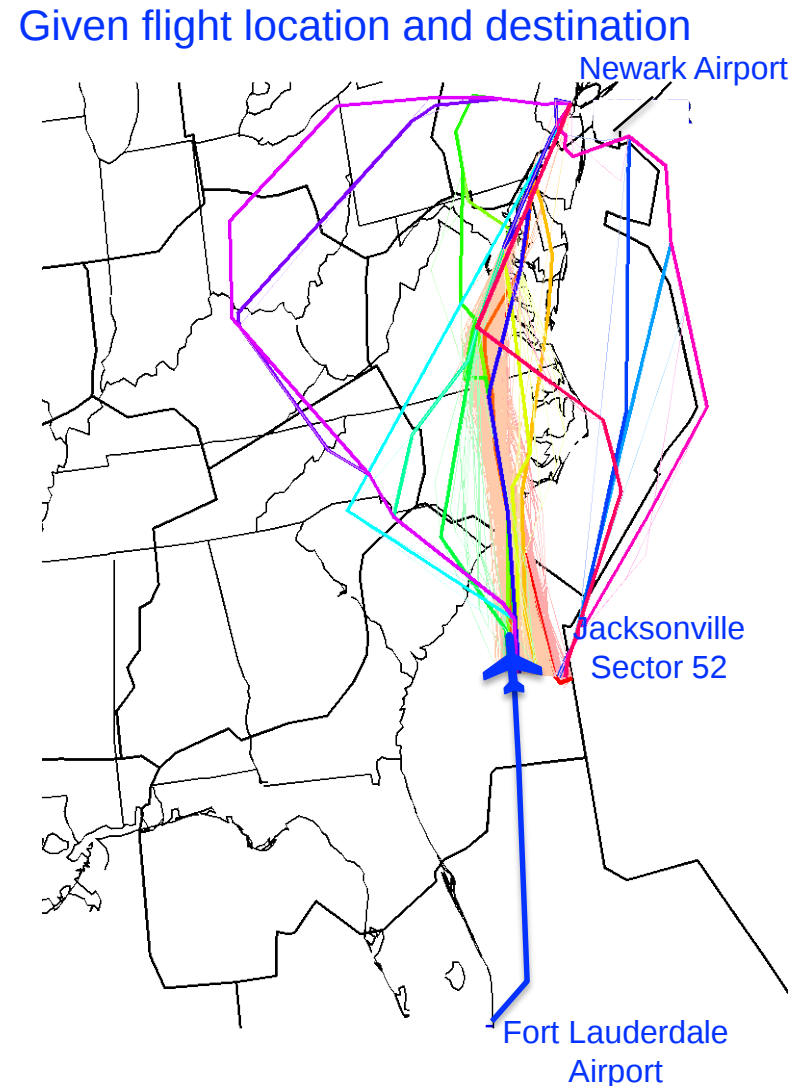
2. Down-Select Trajectory Options

- Apply Hierarchical clustering
- Dissimilarity metric calculated as Euclidean distance between trajectories
- Number of clusters identified based on maximizing avg. Silhouette score
 - For flight from Jacksonville Sector 52 to Newark Airport: 16 clusters
- Most commonly flown trajectory in each cluster identified for further analysis



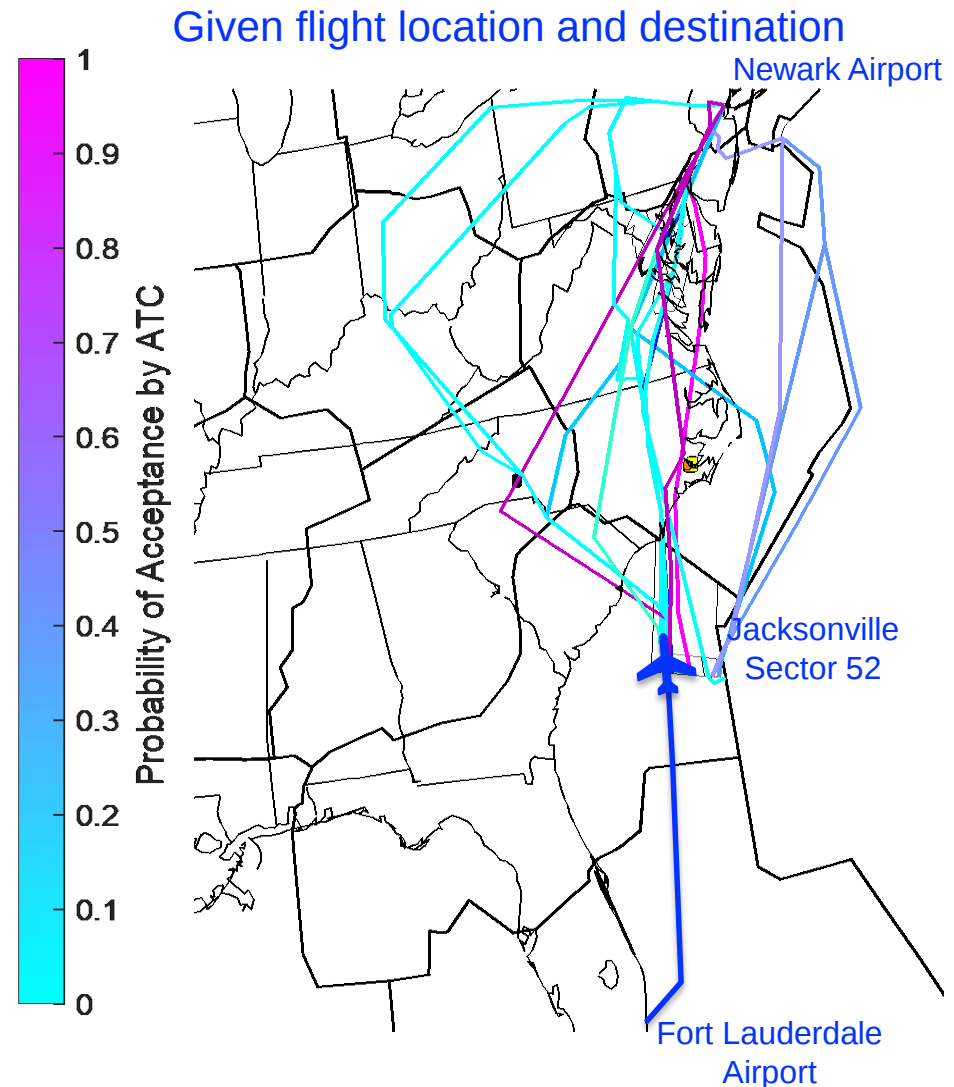
3. Predict Operational Acceptability

- Train machine learning algorithms on historical flight plan amendment data
 - Based on static and dynamic conditions impacting flight
- Select algorithm based on predictive performance using cross validation
- Apply chosen algorithm to predict operational acceptance for down-selected trajectory options



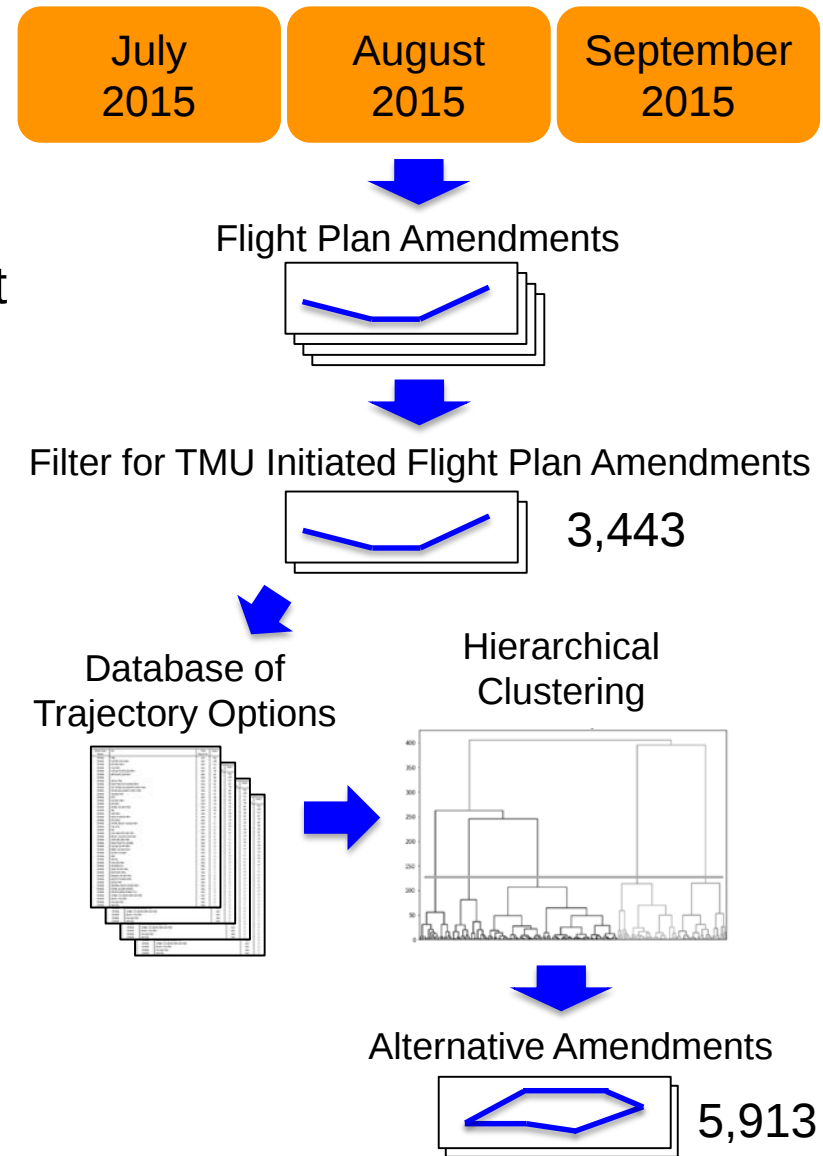
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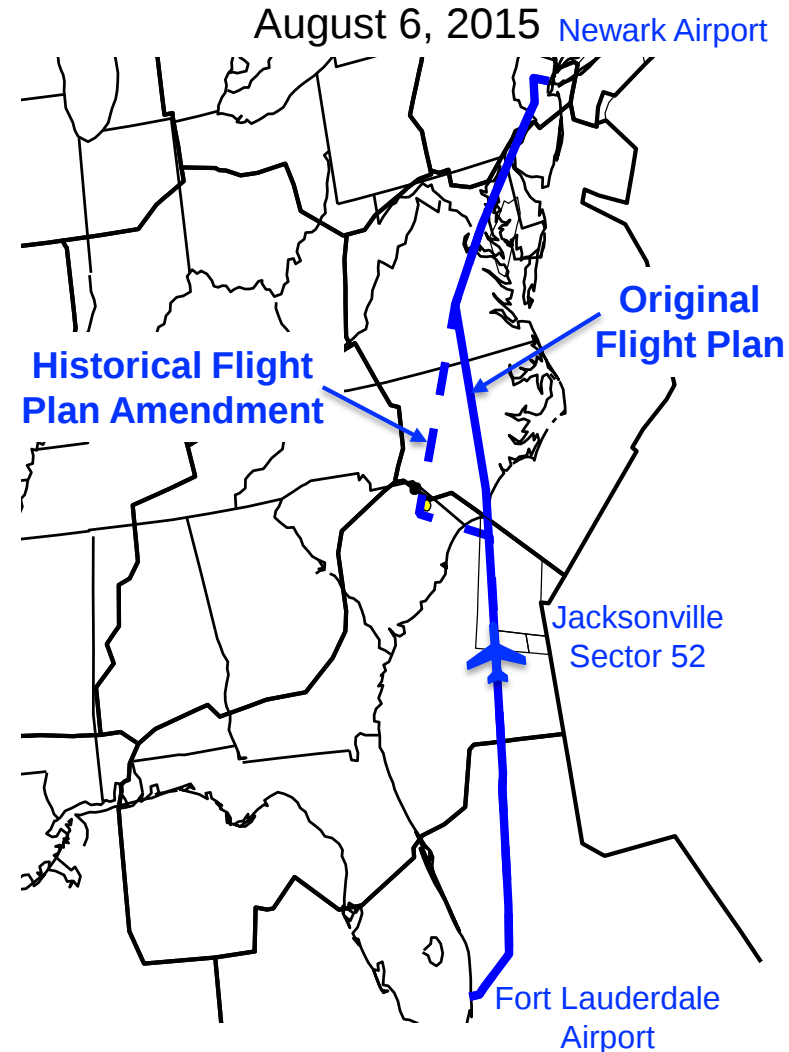
Training Data

- Positive class: Strategic historical flight plan amendments
 - Initiated by Traffic Management Unit (TMU)
 - Filter for amendments:
 - Through multiple Center facilities
 - Excluding direct routings
- Negative class: Generated artificially
 - Potential alternative amendments identified and assumed unacceptable
 - Identified using historical data and clustering



Features

- Static features
 - Historical usage
 - Relative flight duration
- Dynamic features
 - Imbalance between demand and capacity

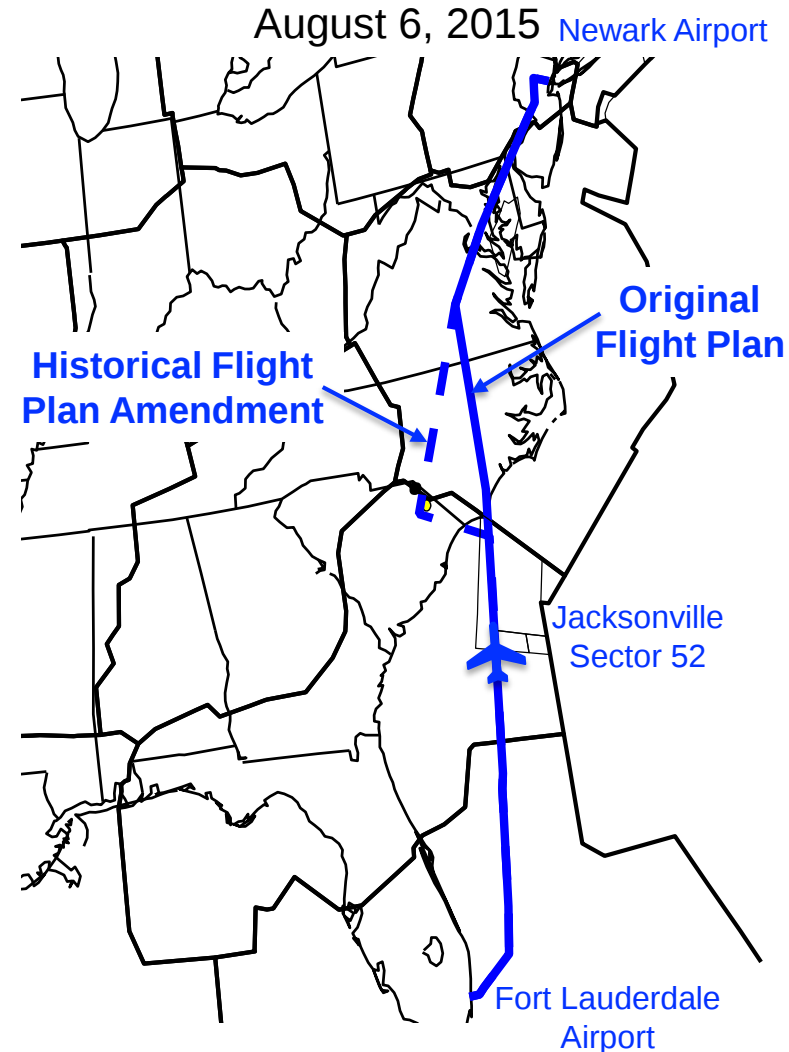


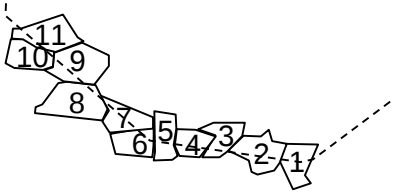


Features

1. Historical Usage

- Count of historical usage
- Count as reroute
- Full trajectory
- Minimum across waypoint pairs
- Difference in counts between original route and amendment

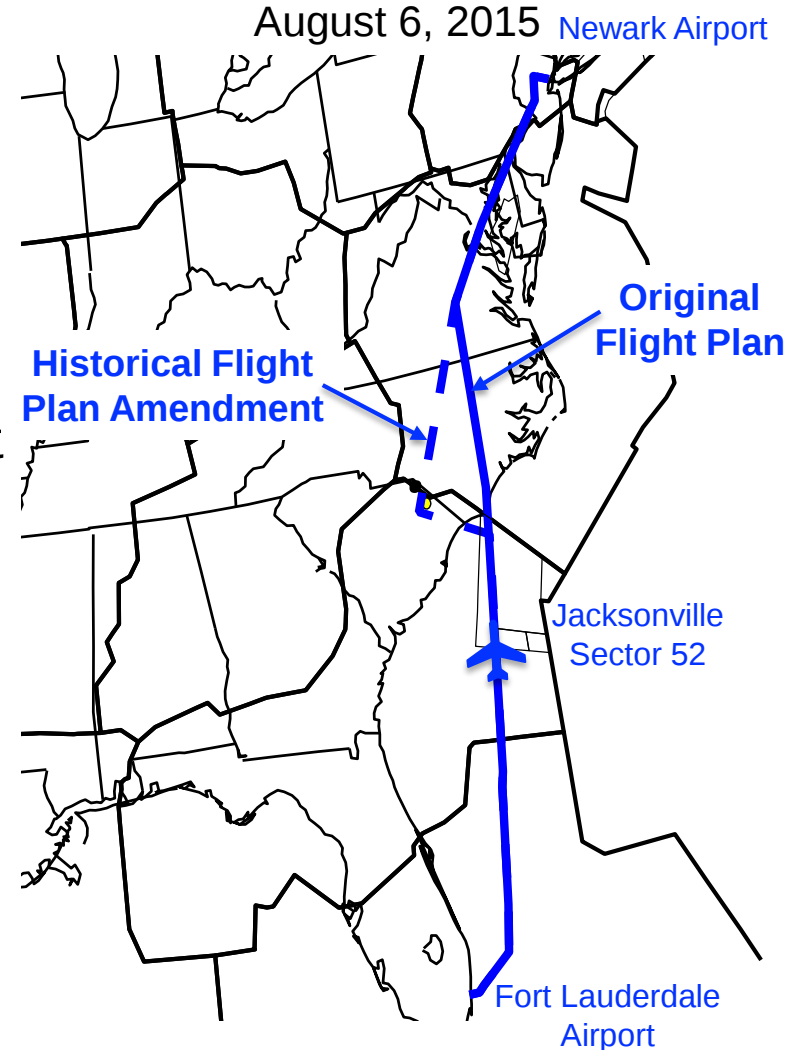


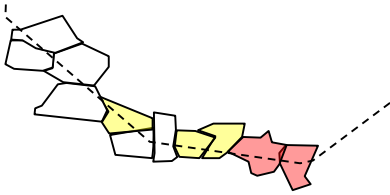


Features

2. Flight Duration

- Flight duration from amendment to destination
- Difference in amendment duration relative to original flight plan
- Number of sectors between amendment and destination
- Difference in number of sectors between amendment and destination relative to original flight plan

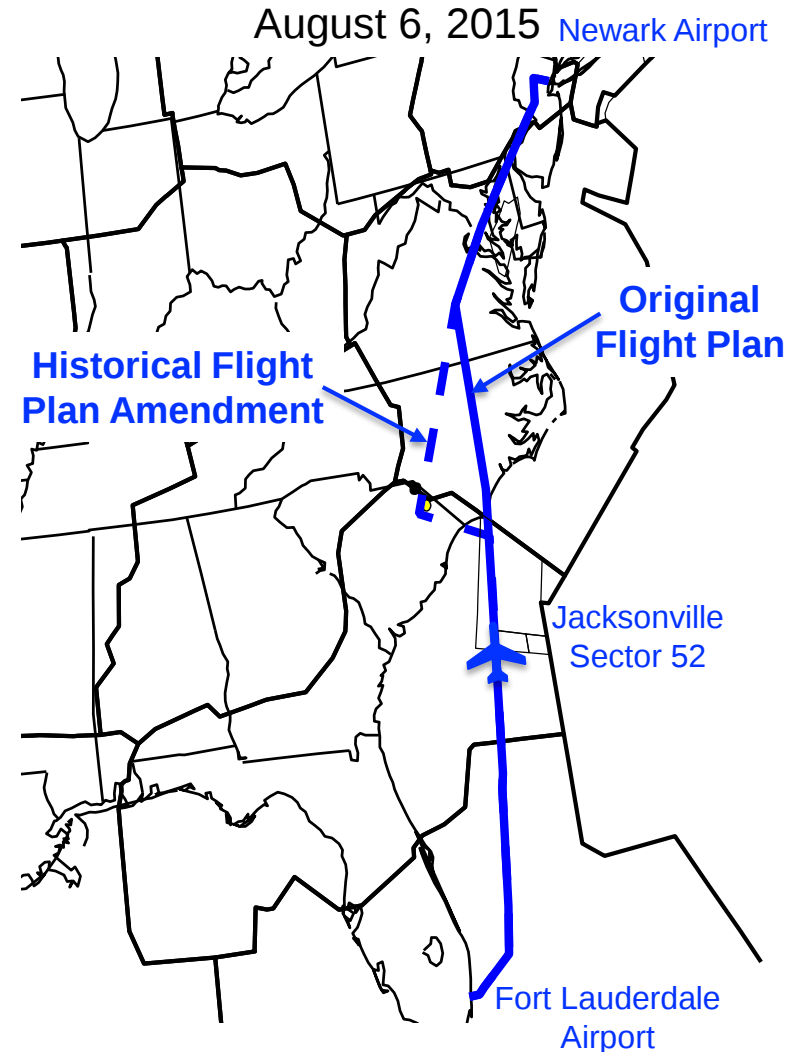


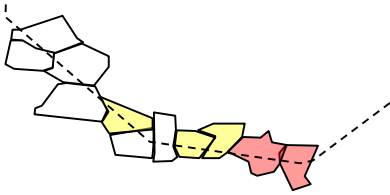


Features

3. Demand to Capacity Imbalance

- Projected demand calculated using NASA Future ATM Concepts Evaluation Tool (FACET)
- Capacity defined by sector Monitor Alert Capacity and weather impact

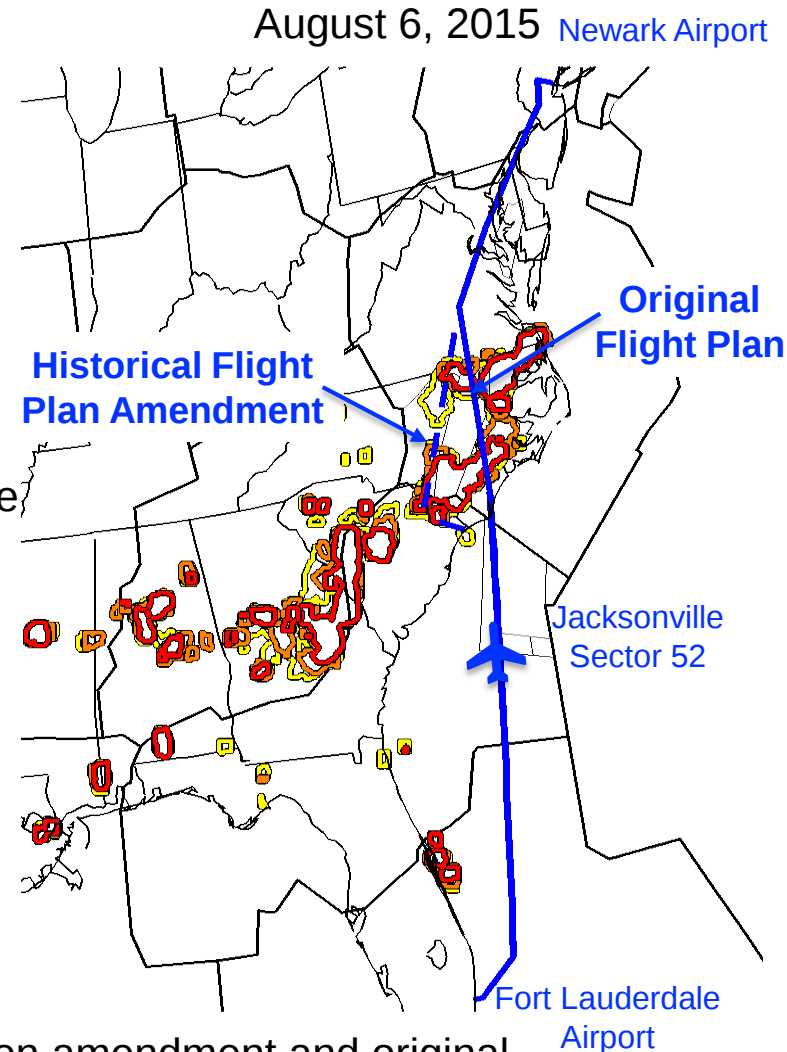




Features

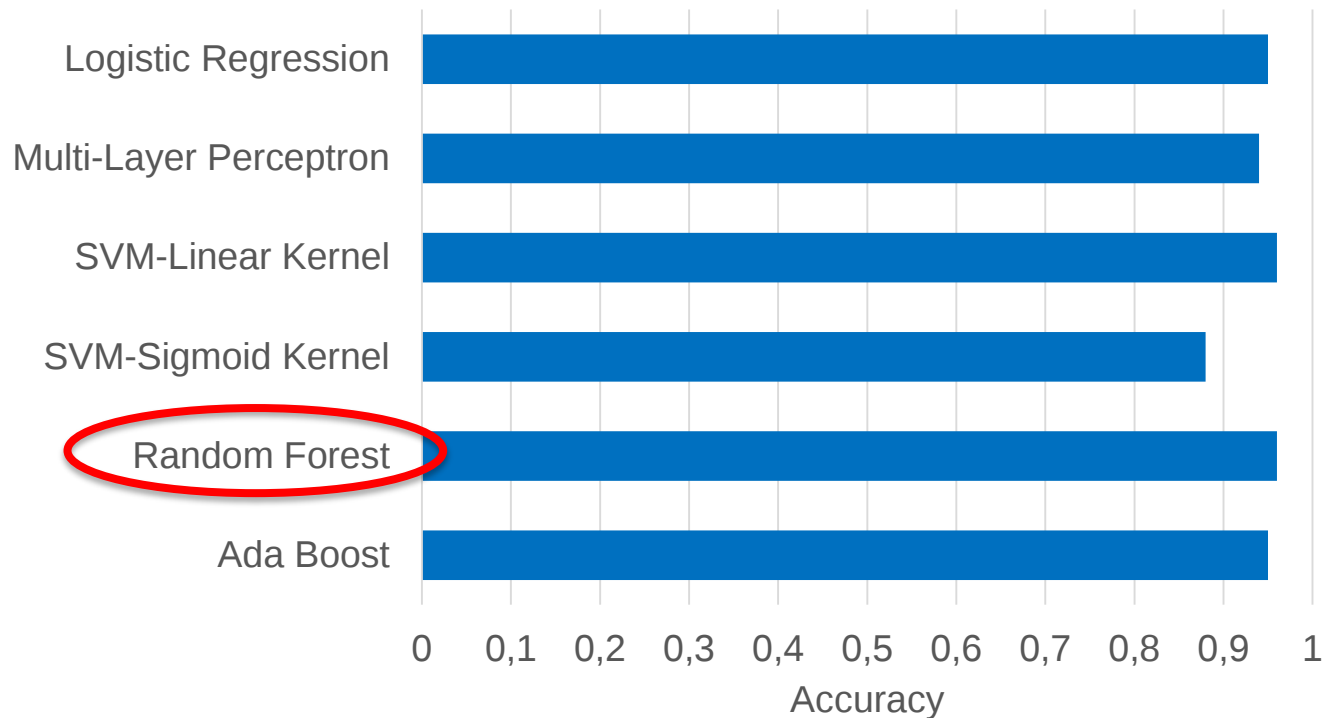
3. Demand to Capacity Imbalance

- Projected demand calculated using NASA Future ATM Concepts Evaluation Tool (FACET)
- Capacity defined by sector Monitor Alert Capacity and weather impact
 - Forecast weather impact based on percentage overlap between sector and Convective Weather Avoidance Model (CWAM) polygons
 - 60%, 70% and 80% probability of deviation CWAM polygons used
- Multiple metrics calculated:
 - Average demand/capacity
 - Maximum demand/capacity
 - Number of sectors over capacity
 - Whether any sector was over capacity
 - Difference between sum of demand/capacity on amendment and original

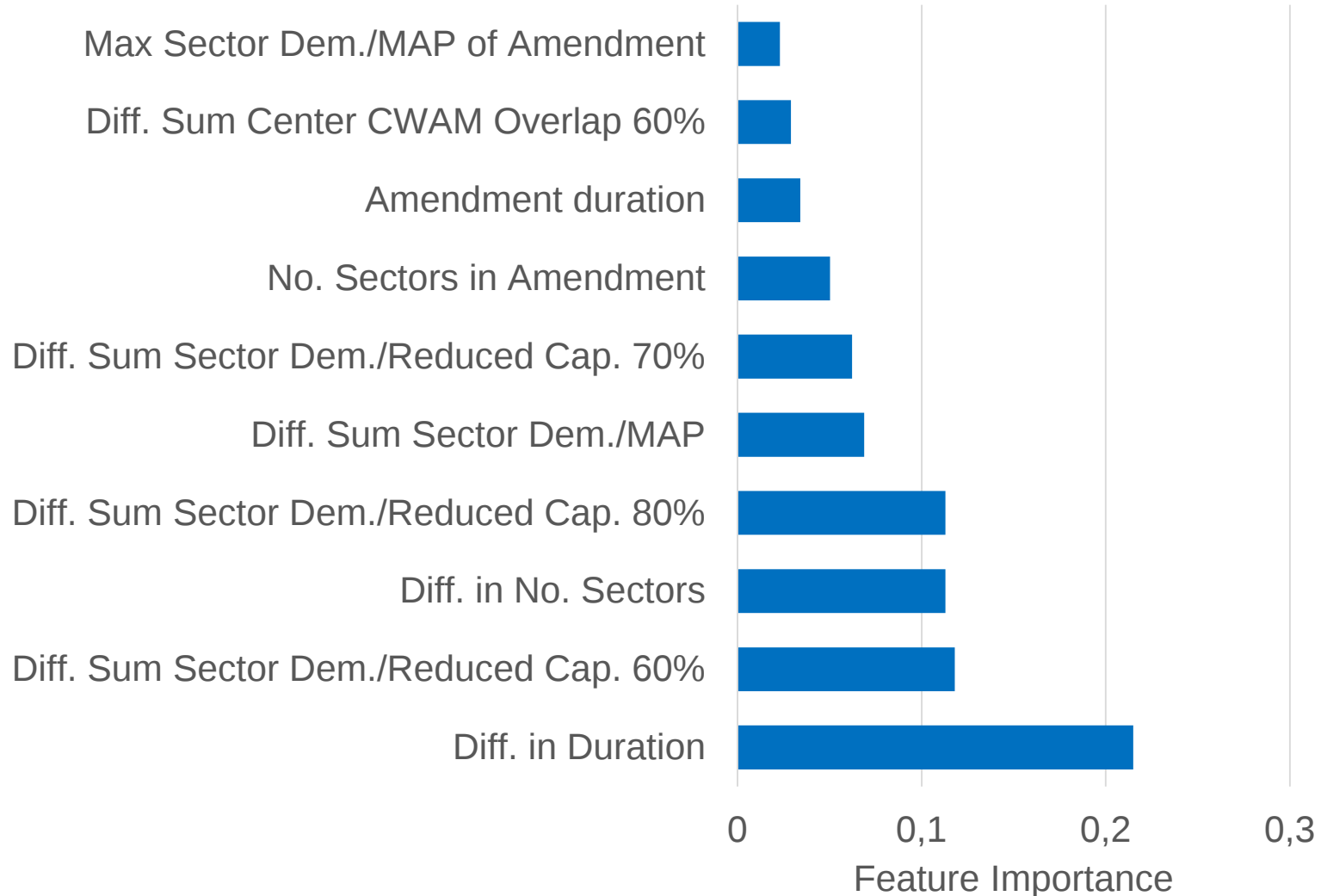


Model Selection

- Model performance estimated using 10-fold cross validation
- 9,356 observations: 36.8% positive, 63.2% negative
- Synthetic Minority Over-Sampling Technique (SMOTE) applied to balance dataset

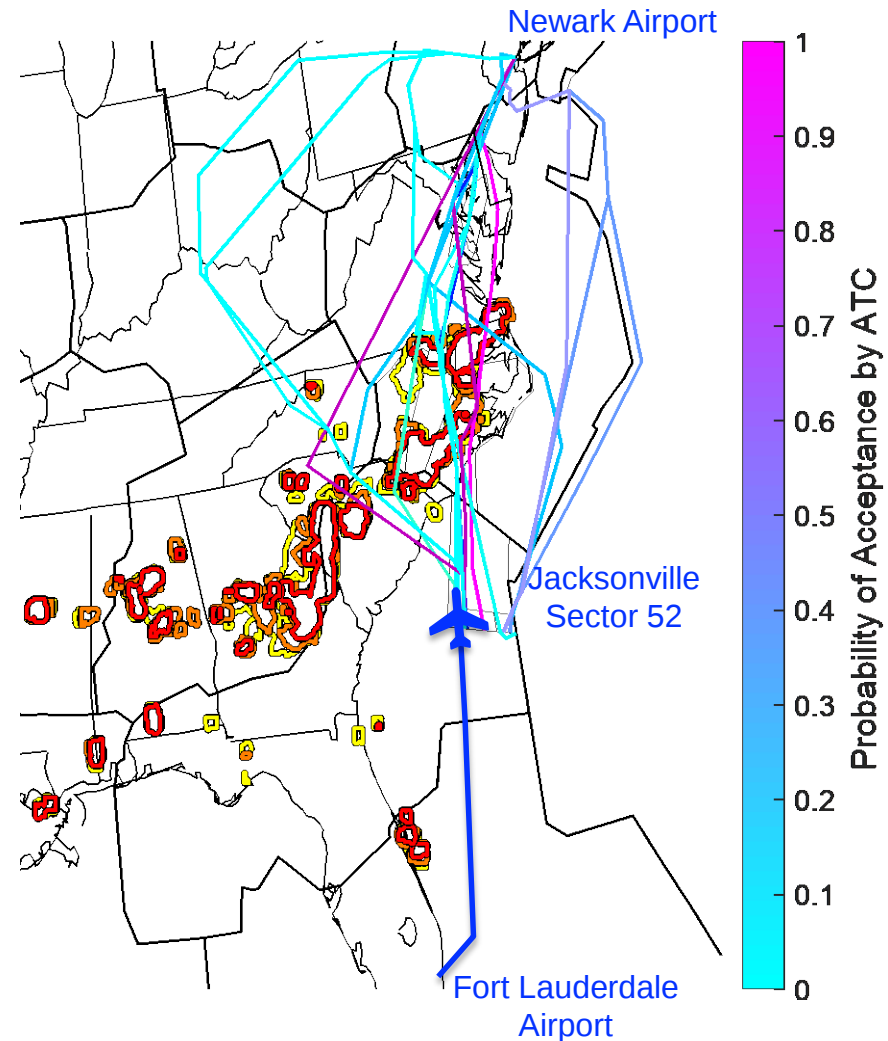


Feature Importance



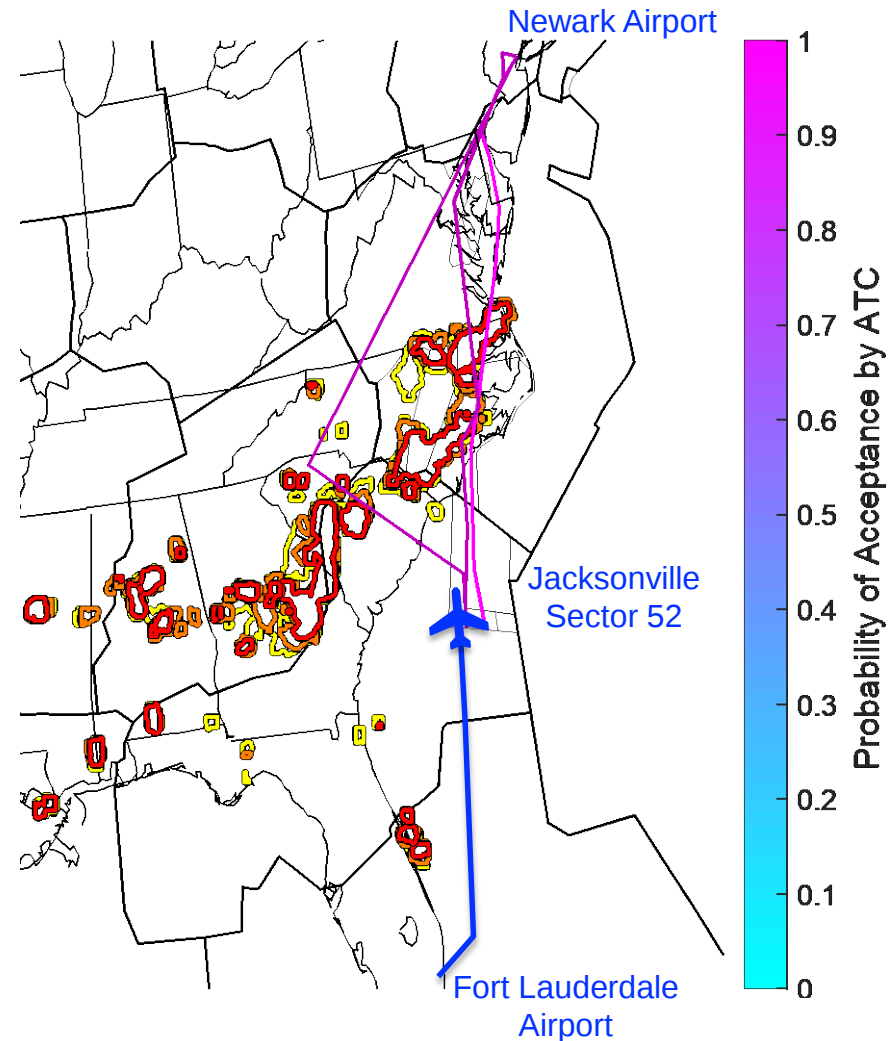
4. Select TOS

- TOS selected based on:
 - Probability of operational acceptance
 - Location of constraint

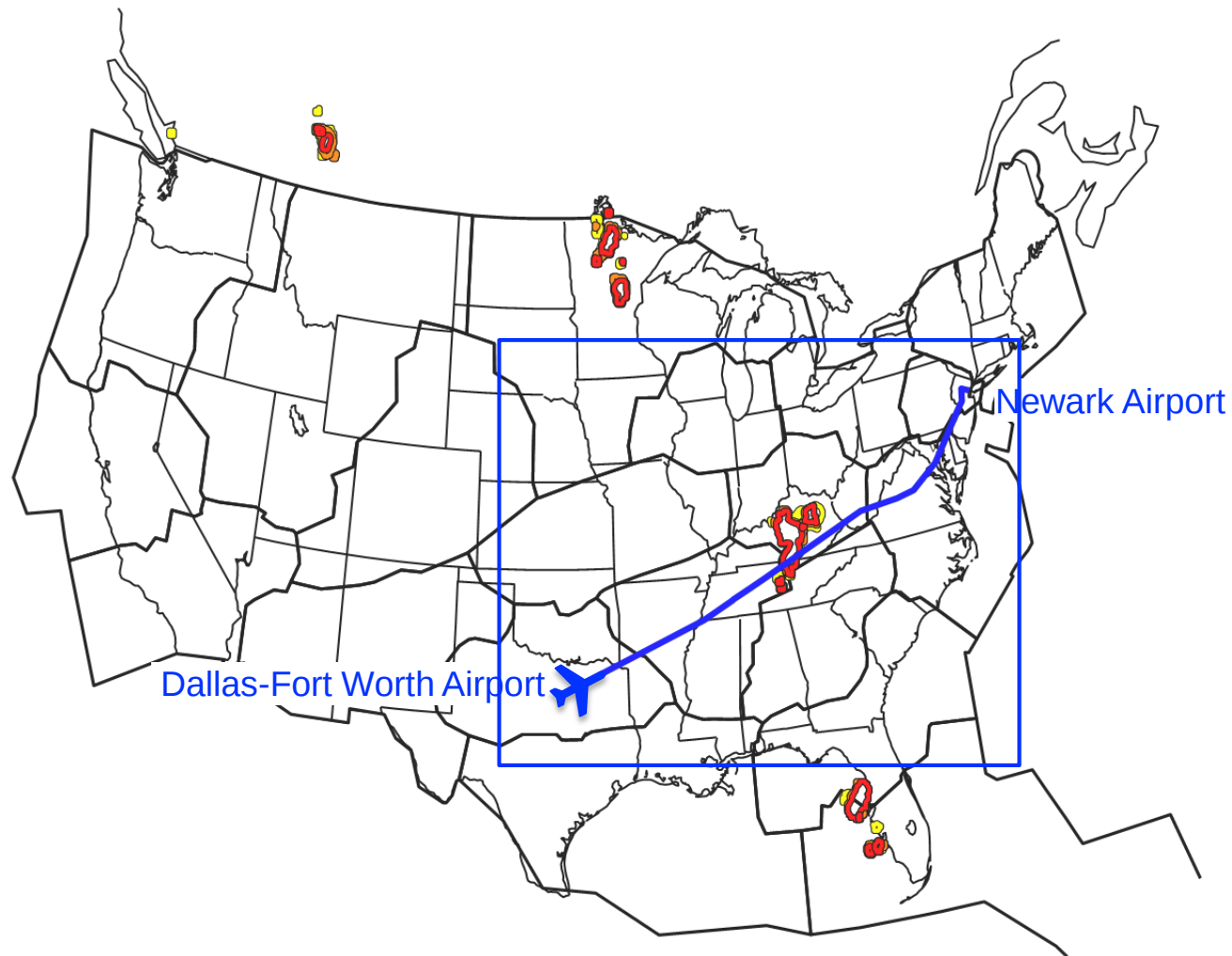


4. Select TOS

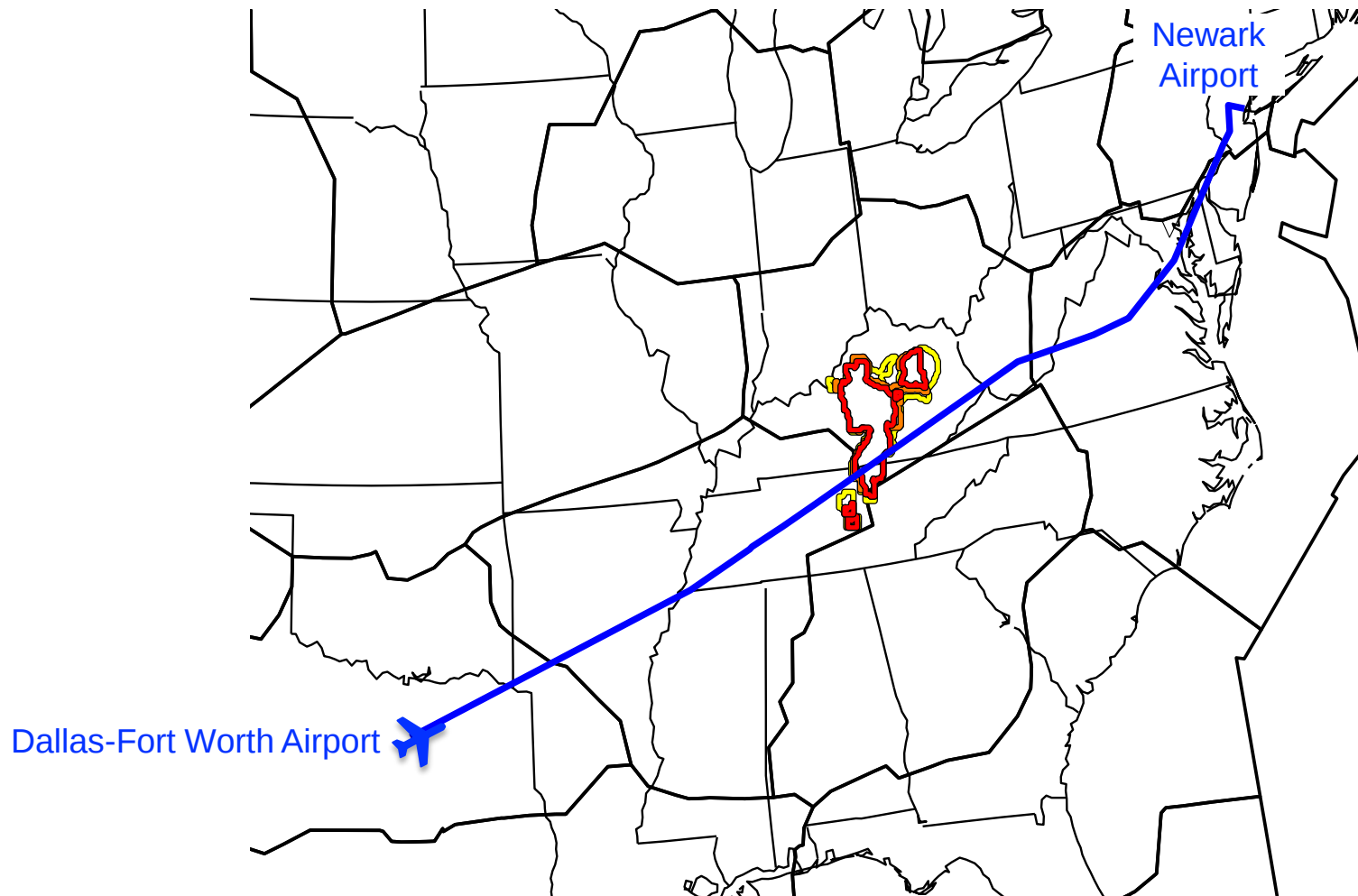
- TOS selected based on:
 - Probability of operational acceptance
 - Location of constraint
- Other factors may also be important
 - Wind optimality
 - Fueling
 - Equipage



Sample Application: Pre-Departure

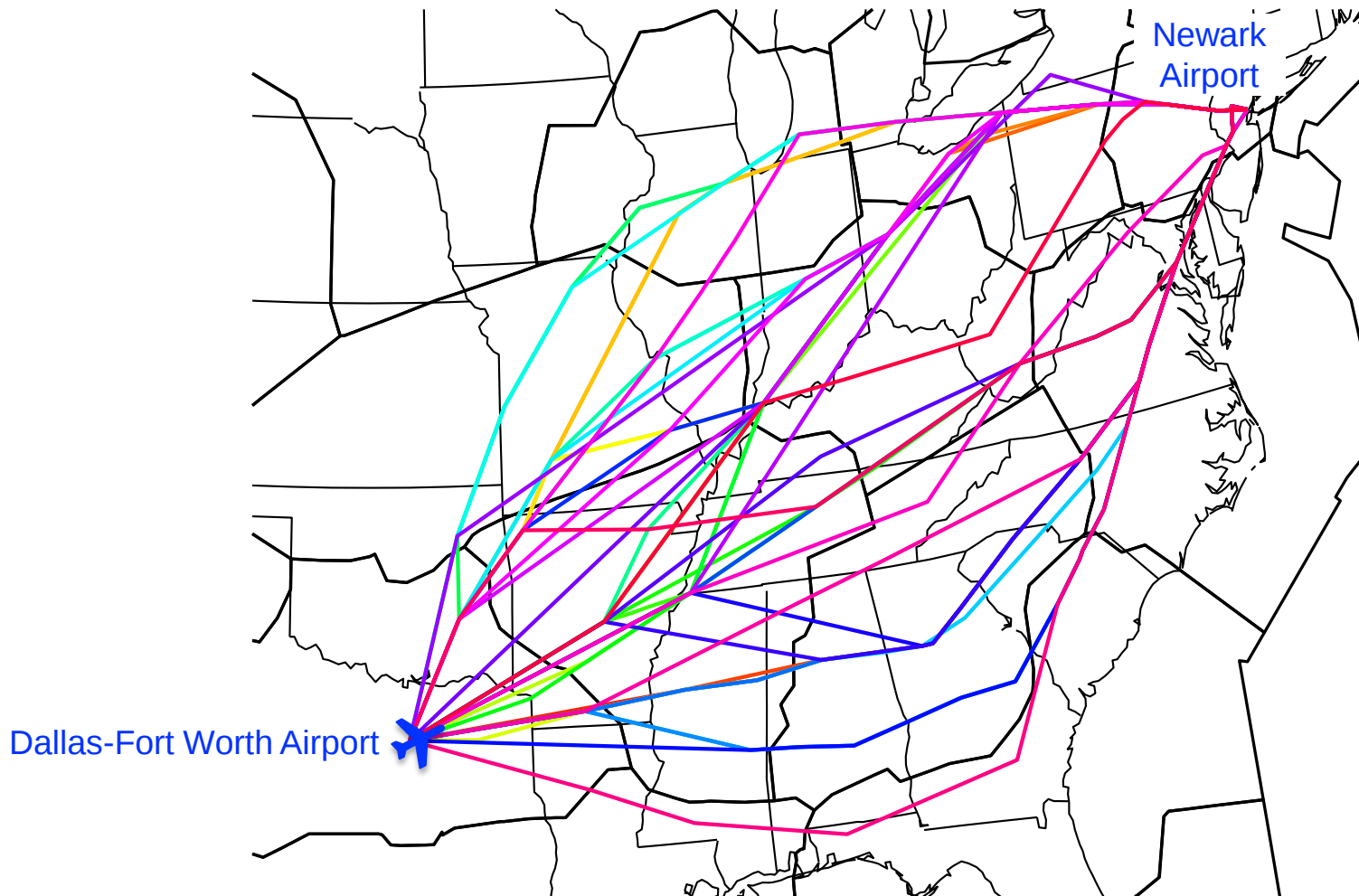


Sample Application: Pre-Departure



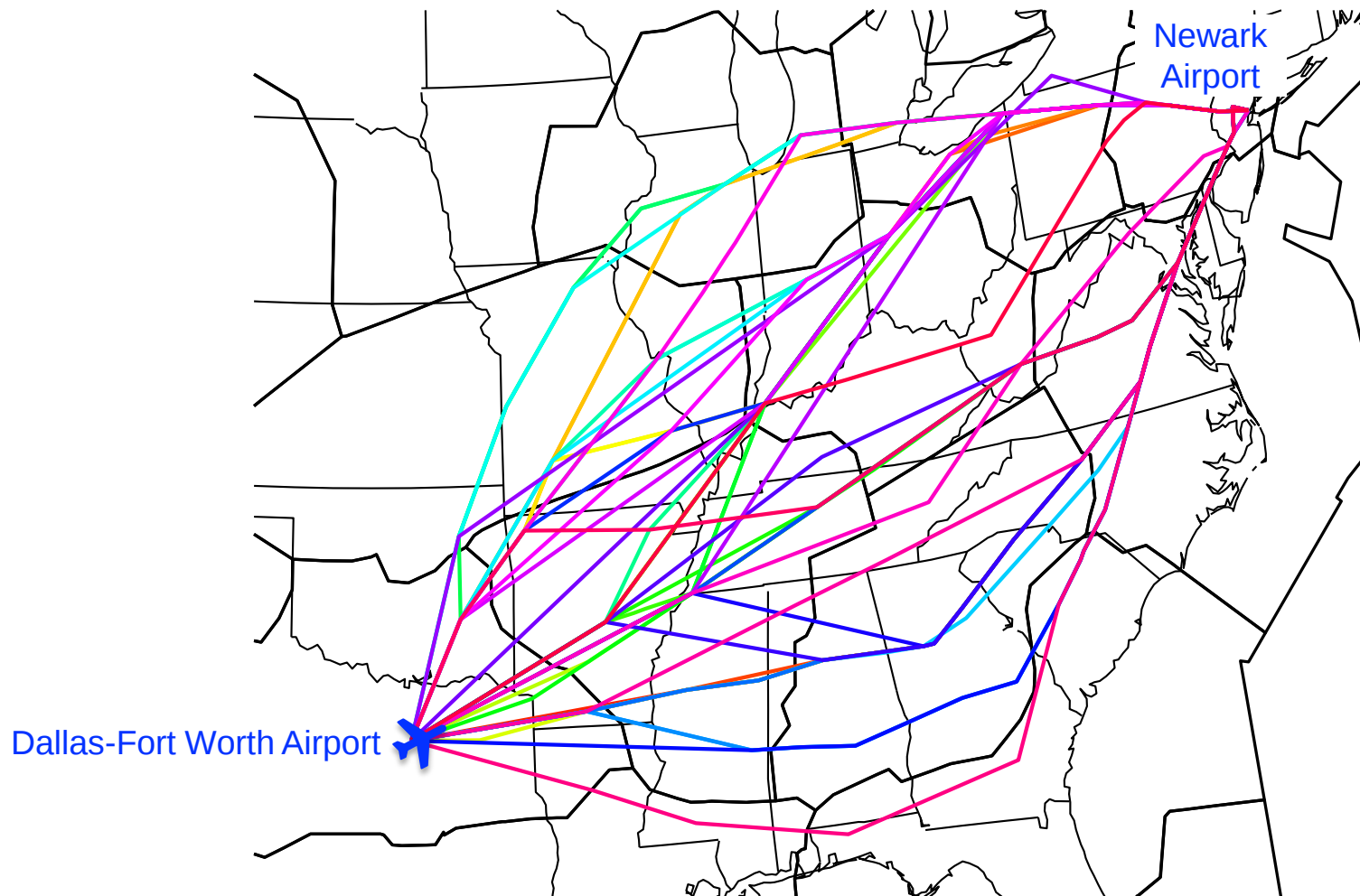
Sample Application: Pre-Departure

1. Identify available trajectory options based on historical routes



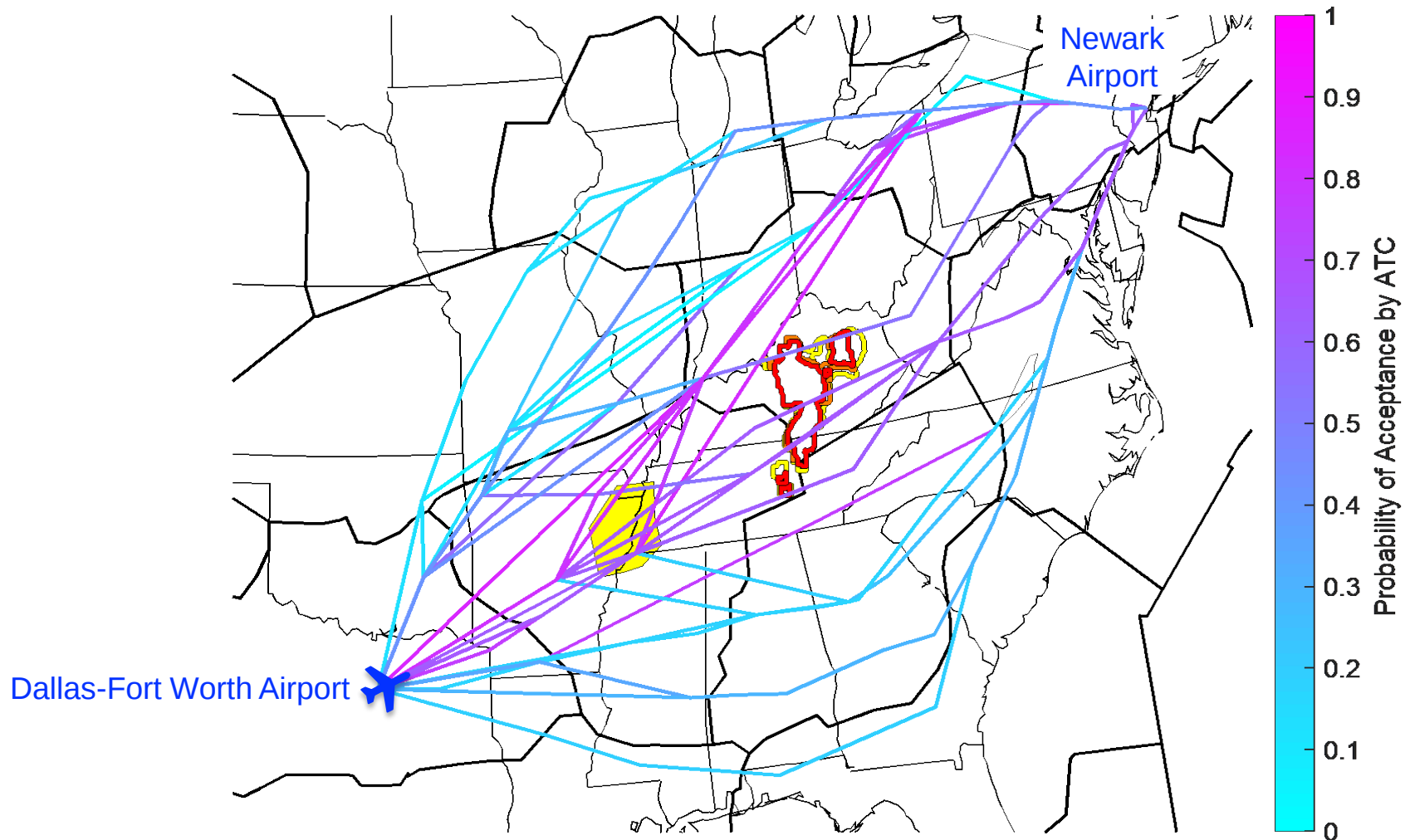
Sample Application: Pre-Departure

2. Down-select trajectory options using clustering



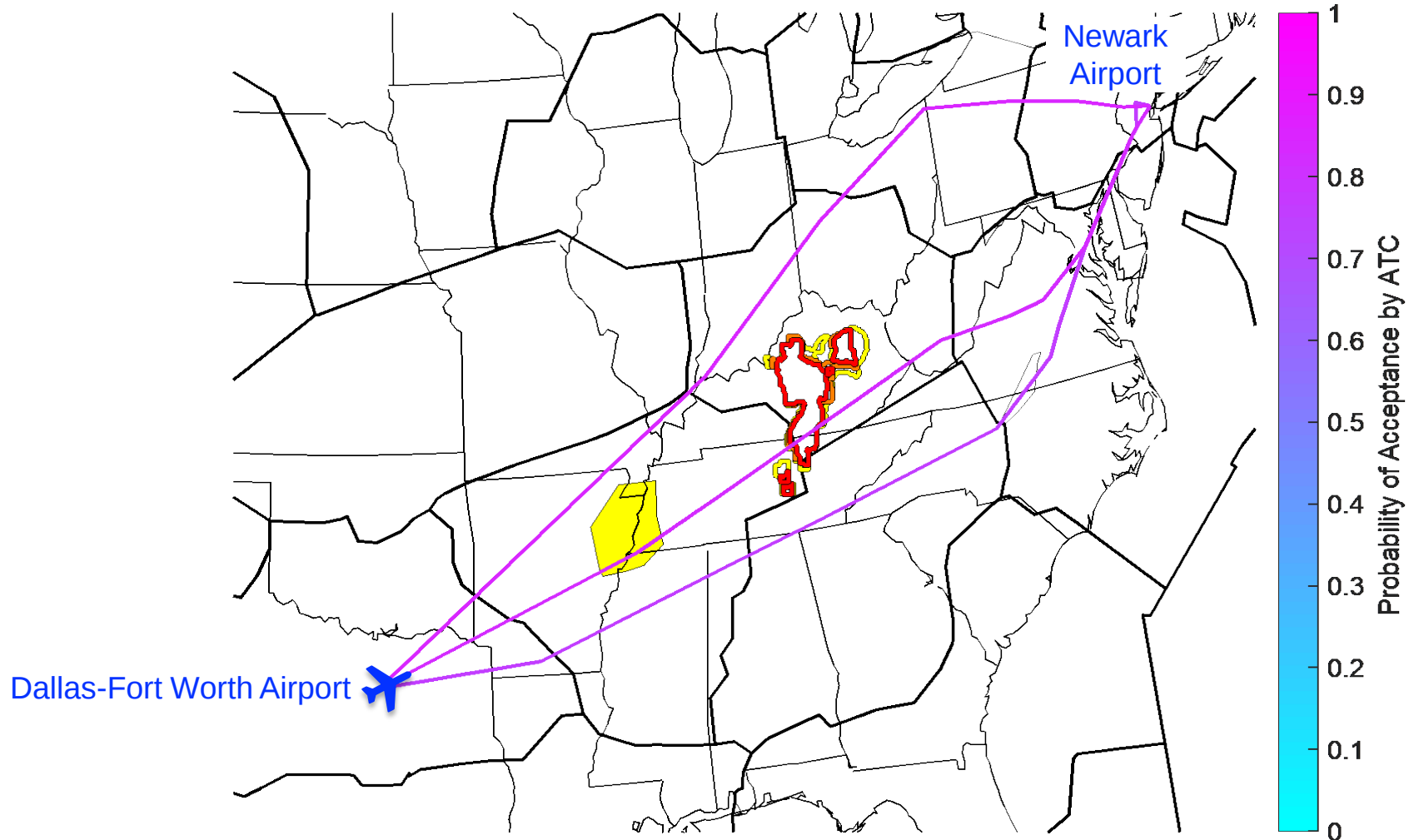
Sample Application: Pre-Departure

3. Predict operational acceptability using machine learning



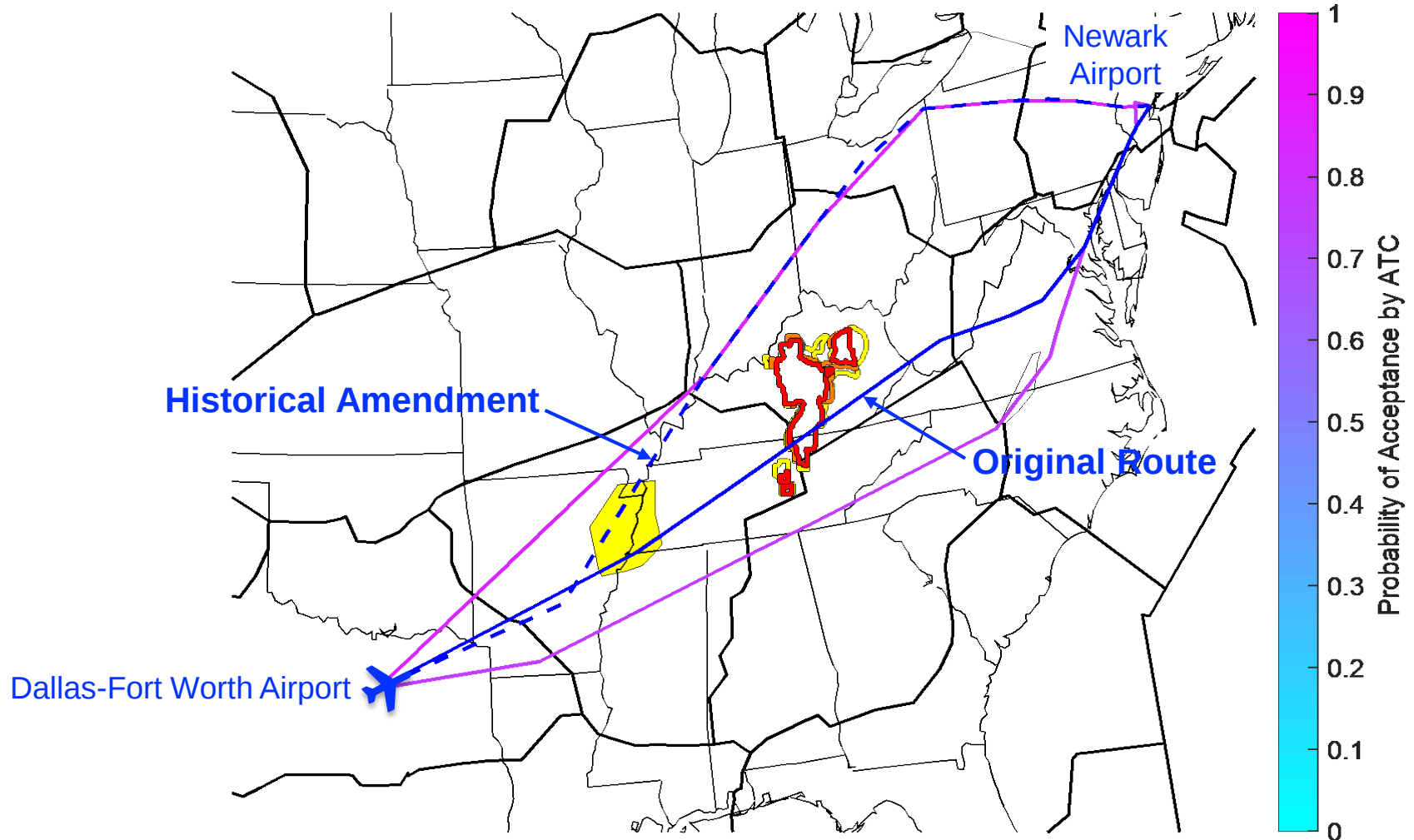
Sample Application: Pre-Departure

4. Select TOS based on operational acceptability and location of constraint



Sample Application: Pre-Departure

4. Select TOS based on operational acceptability and location of constraint



Conclusions

- Machine learning validation results indicate operational acceptability may be predictable with high accuracy
- Approach developed to automatically generate TOSs
 - Incorporated with other capabilities, may be useful in route generation
- Most important features describe difference between amendment and original route for:
 - Flight duration
 - Demand to capacity imbalance
- Could enable more effective trajectory negotiation
 - Could enable flight operators to automatically generate routes with high operational acceptability, and therefore have increased predictability
 - Could enable airlines to effectively submit preferences