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

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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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• Allows trajectory negotiation
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

- Commercial TOS generators under development, accounting for historical usage

- Studies completed on operational acceptability

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

- 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
1. Identify Available Trajectory Options

**Historical Usage**

**Flight Data**

- April 2015
- May 2015
- June 2015

**Flight Plans, Flight Plan Amendments**

**Database of Trajectory Options**

Given flight location and destination

- Newark Airport
- Fort Lauderdale Airport
1. Identify Available Trajectory Options

Historical Usage
Flight Data

April 2015  May 2015  June 2015

Flight Plans, Flight Plan Amendments

Database of Trajectory Options

Given flight location and destination

Newark Airport

Fort Lauderdale Airport

Jacksonville Sector 52

Given flight location and destination
1. Identify Available Trajectory Options

Historical Usage

Flight Data

April 2015  May 2015  June 2015

Flight Plans, Flight Plan Amendments

Database of Trajectory Options

Given flight location and destination

Newark Airport

Jacksonville Sector 52

Fort Lauderdale Airport
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

Given flight location and destination
- Jacksonville Sector 52
- Fort Lauderdale Airport
- Newark Airport

Diagram showing flight paths and locations.
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

\[
\begin{align*}
  \mathbf{tr}_i &= (x_{i1}, y_{i1}, x_{i2}, y_{i2}, \ldots, x_{iN}, y_{iN}) \\
  \mathbf{tr}_j &= (x_{j1}, y_{j1}, x_{j2}, y_{j2}, \ldots, x_{jN}, y_{jN}) \\
  \vdots \\
  d_{ij} &= \sqrt{(x_{i1} - x_{j1})^2 + (y_{i1} - y_{j1})^2 + \ldots + (x_{iN} - x_{jN})^2 + (y_{iN} - y_{jN})^2}
\end{align*}
\]
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

Given flight location and destination

Jacksonville Sector 52

Fort Lauderdale Airport

Newark Airport
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Given flight location and destination:
- Jacksonville
- Sector 52
- Fort Lauderdale Airport
- Newark Airport
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
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
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- 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

Accuracy

- Logistic Regression
- Multi-Layer Perceptron
- SVM-Linear Kernel
- SVM-Sigmoid Kernel
- Random Forest
- Ada Boost
Feature Importance

- Max Sector Dem./MAP of Amendment
- Diff. Sum Center CWAM Overlap 60%
- Amendment duration
- No. Sectors in Amendment
- Diff. Sum Sector Dem./Reduced Cap. 70%
- Diff. Sum Sector Dem./MAP
- Diff. Sum Sector Dem./Reduced Cap. 80%
- Diff. in No. Sectors
- Diff. Sum Sector Dem./Reduced Cap. 60%
- Diff. in Duration
4. Select TOS

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

- Other factors may also be important
  - Wind optimality
  - Fueling
  - Equipage
Sample Application: Pre-Departure
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1. Identify available trajectory options based on historical routes

![Map showing flight routes between Dallas-Fort Worth Airport and Newark Airport]
Sample Application: Pre-Departure

2. Down-select trajectory options using clustering
Sample Application: Pre-Departure

3. Predict operational acceptability using machine learning

Dallas-Fort Worth Airport

Newark Airport

Probability of Acceptance by ATC
Sample Application: Pre-Departure

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

- Newark Airport
- Dallas-Fort Worth Airport
Sample Application: Pre-Departure

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

Dallas-Fort Worth Airport

Newark Airport

Historical Amendment

Original Route
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