Predicting Aircraft Trajectory Choice – A Nominal Route Approach

Yulin Liu, Mark Hansen
University of California, Berkeley

David Lovell, Michael Ball
University of Maryland, College Park

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Outline

• Introduction
• Data Sources
• Methodology
• Results
Introduction (I)

• FAA and EUROCONTROL published metrics to evaluate the flight en route inefficiency, and FAA is seeking to understand the causal factors behind the inefficiency.
• Observe rich variety of route choices that differ drastically with respect to en route inefficiency.
• We want to understand the features that affect the choice of route for a flight.

Reference:
Introduction (II)

• Applications
  – Performance analysis
    • Role of route choice in determining flight en route inefficiency.
  – Sector demand analysis
    • Trajectory prediction tools that incorporate features such as weather and wind can make more accurate traffic load estimation.
  – TMI planning
    • A more reliable sector demand forecast can support better TMI decision making.
Introduction (III)

Why green?
Outline

• Introduction
• Data Sources
  • Methodology
• Results
Data Sources

- Flight Track Data (TFMS)
  - 60-second update
  - Currently we focus on 5 pairs: IAH ↔ BOS, JFK ↔ FLL and LAX → SEA
- Miles-In-Trail (MIT) Data from National Traffic Management Log (NTML)
- Quality Controlled Local Climatological Data (QCLCD) from NOAA
  - Hourly presence of certain types of convective weather (ground-based)
- Wind data from National Center for Atmospheric Research (NCAR)
Flight Track Data

- Trajectories from IAH to BOS in 2013.
- Trajectories (red curves) show obvious clustering patterns in the airspace.
- Not all trajectories were following the ATC preferred routes.
Outline

• Introduction
• Data Sources
• Methodology
• Results
Overview

• As the first stage of the research, we want to predict, instead of the individual flight tracks, the choice of flight route from a finite set of alternatives.
• These predictions can support individual flight trajectory prediction tools by compressing useful features.
• Predictive models can identify the relative importance of disparate factors and enhance our understanding of air flow patterns.
Methodology

Constructing Route Choice Set
- Trajectory clustering algorithm

Feature Engineering
- Dimension reduction
- Efficient matching algorithm

Predictive Models and Model Selection
- Build different predictive models
- Select models with the best performance
Constructing Choice Set

• Choice set needs to be small and representative.
Constructing Choice Set

- Choice set needs to be small and representative.
- Trajectory clustering algorithm helps us consolidate large volume of flight tracks into a small set of clusters.
- Flights within the same cluster are similar to each other, and flights that are unusual will be classified as outliers.
Clustering Algorithms

• **Step 0: Trajectory Cleaning**
  – Exclude both spatial and temporal discontinuity trajectories;
  – Exclude trajectories starting/ending outside terminal areas.

• **Step 1: Trajectory resampling**
  – Get trajectories with equal numbers of points;
  – Linear Interpolation (with respect to distance flown);
  – Each trajectory is represented by 100 points.

• **Step 2: Principal Component Analysis (PCA)**
  – Dimension reduction & Trajectory smoothing;
  – First five components can capture more than 90% of variations.

• **Step 3: DBSCAN Clustering**
  – Trajectory classifications;
  – DBSCAN algorithm is applied to the PCA components to get representative clusters.
Finding Representative Routes

• For each cluster, we solve a “1-median problem” to find the “representative route”.
• The representative routes are actual flown 4d trajectories.
  \[ RR = \{(lat_0, lon_0, alt_0, t_0), (lat_1, lon_1, alt_1, t_1), \ldots\} \]
IAH → BOS (5062 Flights in Total)

Black curves are classified as outliers
White Solid curves are Representative Routes

Weights

Boxplot of Enroute Inefficiency for Different Clusters

34.12% 22.55% 35.76% 0.553% 0.553% 6.458%
IAH $\rightarrow$ BOS (5222 Flights)

Black curves are classified as outliers
White Solid curves are Representative Routes

DBSCAN applied to PCA mode matrix

Boxplot of Enroute Inefficiency for Different Clusters

Weights:
- 60.37%
- 5.46%
- 19.18%
- 2.64%
- 1.26%
- 11.06%
Three More Pairs

FLL → JFK

JFK → FLL

LAX → SEA
Feature Engineering (I)

• Presence of convective weather, such as thunderstorm, rain and hail.
• Wind condition.
• MIT restrictions.
• Flight-associated characteristics, such as departure season and airline.
Convective Weather Data

Thunderstorm and rain condition from 08/08/2013 18:00:00 to 08/08/2013 21:00:00 Z

- WBAN Station
- Thunderstorm
- Rain
Forecast Wind Data

Wind Field Diagram (m/s) @ 200 mbar (~38,000 ft.); 02/04/2013 18:00 Zulu

17 isobaric pressure levels
For each level, the resolution is 2.5° by 2.5° lat/lon.
Miles-In-Trail Data

- Miles-in-trail specifies the minimal required distance between two consecutive aircrafts.
- Apportion traffic into a manageable flow.

**ZDV** is trying to protect **ZLC**, which is overloaded, by providing a MIT (e.g., 15 miles) to separate aircrafts through the Navaid **ONL**.
Feature Engineering (II)

- Nominal route: “representative” of a cluster.
- Use nominal routes as the basis for determining flight features that help predict which cluster the flight belongs to.
Feature Engineering (II)

• Nominal route: “representative” of a cluster.
• Use nominal routes as the basis for determining flight features that help predict which cluster the flight belongs to.
• For each flight, we assume it will choose from one of the clusters. Thus, we match the *hypothetical exposure* of a particular flight to convection, MIT restrictions, and wind, if it had used any one of the nominal routes, assuming its *actual departure time*.
Feature Engineering (III)

Choose one of the nominal routes

Replace the departure time and subsequent time stamps

Nominal Route 1
Nominal Route 2
...
Nominal Route $N$

Flight $i$, Departure time $t_i$

Convection
Wind
MIT

Route 1’ Features
Route 2’ Features
...
Route $N’$ Features

Append together
Feature Engineering (III)

**Flight** $i$

**Departure time** $t_i$

**Nominal** Route 1

**Nominal** Route 2

... 

**Nominal** Route $N$

**Nominal** Route 1'

**Nominal** Route 2'

... 

**Nominal** Route $N'$

*Replace the departure time and subsequent time stamps*

**Convection**

**Wind**

**MIT**

**Route 1’ Features**

**Route 2’ Features**

... 

**Route $N'$ Features**

Choose one of the nominal routes

Append together
**Feature Engineering (III)**

- **Flight**: $i$
- **Route**: Nominal Route 1, Nominal Route 2, ..., Nominal Route $N$

**Departure time** $t_i$:
- Replace the departure time and subsequent time stamps

**Convection**, **Wind**, **MIT**

**Nominal Route $1'$**, **Nominal Route $2'$**, ..., **Nominal Route $N'$**: Matching

- **Choose one of the nominal routes**
- **Query-and-vectorization – tree-based query**
- **Time-space trade-off – batch mode operation**

**Append together**

Route $1'$ Features, Route $2'$ Features, ..., Route $N'$ Features
Feature Engineering (III)

Flight $i$

Departure time $t_i$

Convection

Wind

MIT

Nominal Route 1

Nominal Route 2

... 

Nominal Route $N$

Nominal Route 1'

Nominal Route 2'

... 

Nominal Route $N'$

Replace the departure time and subsequent time stamps

Choose one of the nominal routes

Append together

Route 1’ Features

Route 2’ Features

Route $N'$ Features
Feature Engineering (III)

```
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<th>Spring</th>
<th>Summer</th>
<th>Fall</th>
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<td>0.1015</td>
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</tbody>
</table>
```
Matching – Convective Weather

- For each track point on the trajectory, find all the stations within a circle with radius $r$ (150 nmi).
Matching – Convective Weather

- Weighted average the weather variable (binary) for stations within the circle, and the weight is proportional to the inverse of the distance.
- Metric: average of the weather exposure for all track points along the route.
Matching – Convective Weather

- Weighted average the weather variable (binary) for stations within the circle, and the weight is the proportional to the inverse of the distance.

\[ W_{x_t} = \sum_i I_i \cdot \frac{d_i}{\sum_j d_j} \]

- Metric: average of the weather exposure for all track points along the route.

\[ Wx = \frac{1}{T} \cdot \sum_t W_{x_t} \]
Matching – Wind

For each track point, find the nearest 4d reference point of the wind data file.

Assign the wind speed (vertical and horizontal) of the nearest grid to the track point.

Wind Field Diagram (m/s) @ 200 mbar (~ 38,000 ft.)
02/04/2013 18:00 Zulu
Matching – Wind

Wind Field Diagram (m/s) @ 200 mbar (~38,000 ft.)
02/04/2013 18:00 Zulu

- Calculate the headwind/tailwind speed for each track point, based on heading derived from previous track point
- Metrics
  - Equivalent still air distance
  - Average wind speed along the route.
Matching – MIT

- A given nominal route, with adjusted departure time, is assumed to be affected by an MIT if:
  - It crosses the MIT facilities
  - It crosses the NAS element or follows the jet route to which the MIT applies
  - Its crossing time is within the time the MIT is in effect
  - Its crossing altitude is covered by the restriction
Matching – MIT

- **Metrics:**
  - Number of MITs along the route
  - Average of MIT value, duration and stringency (product of MIT value and duration)
Predictive Models

• Objective
  – For any flight, given the feature space (e.g., weather, wind, and MIT), predict to which cluster it belongs.

• Candidate models
  – Random Forest, Logistic Regression, Gradient Boosting, and SVM.
  – Hyperparameter tuning: grid search and 3 fold cross validation.

• Model selection
  – Average F1 score on testing set (20% of total dataset).
Metrics

• F1 score
  – Confusion matrix
  – precision = \( \frac{TP}{TP+FP} \)
  – recall = \( \frac{TP}{TP+FN} \)
  – \( F_1 = 2 \times \frac{\text{precision} \times \text{recall}}{\text{precision} + \text{recall}} \)
Outline

• Introduction
• Data Sources and Preliminary Statistical Analysis
• Methodology
• Results
Results – Model Selection

Max F1 scores are good in general.

Min F1 scores differ significantly across models – RF and LR in general are better.

RF outperforms the others for all pairs except IAH → BOS, for which GB has slightly better average F1 score.

### TABLE VI: MODEL PERFORMANCE

<table>
<thead>
<tr>
<th>Model</th>
<th>OD pair</th>
<th>IAH</th>
<th>BOS</th>
<th>JFK</th>
<th>LAX</th>
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<tr>
<td></td>
<td></td>
<td>BOS</td>
<td>IAH</td>
<td>FLL</td>
<td>JFK</td>
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<tr>
<td>LR</td>
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<td>C=0.1</td>
<td>C=1</td>
<td>C=150</td>
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<td></td>
<td>F1 max</td>
<td>0.53</td>
<td>0.73</td>
<td>0.88</td>
<td>0.87</td>
</tr>
<tr>
<td></td>
<td>F1 min</td>
<td>0.00</td>
<td>0.11</td>
<td>0.07</td>
<td>0.00</td>
</tr>
<tr>
<td></td>
<td>F1 mean</td>
<td>0.28</td>
<td>0.32</td>
<td>0.34</td>
<td>0.25</td>
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<td>C=150</td>
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<td>F1 max</td>
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<td>0.74</td>
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<td>0.89</td>
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<td>F1 mean</td>
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<td>0.30</td>
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<td>F1 mean</td>
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<tr>
<td></td>
<td>F1 mean</td>
<td>0.29</td>
<td>0.30</td>
<td>0.35</td>
<td>0.27</td>
</tr>
</tbody>
</table>
Wind has the highest impact on the route choice, followed by thunderstorm and rain.

Other meteorological conditions seem to have negligible effect.

MIT has moderate effect in both cases.

Airline has very limited effect, since over 95% of the traffic comes from the United Airlines.
Results – Feature Importance

- Wind, rain and thunderstorm have similar effect as the previous pairs, however, MIT has higher effect in these two pairs.
- As the market is less concentrated (JetBlue gets around 70% traffic, and Delta gets another 25%), airline effect is slightly more important.
Results – Feature Importance

Wind has the strongest effect here, followed by rain and thunderstorm.
MIT barely plays a role for this pair.
Market is less concentrated (Alaska gets 55%, Virgin gets 15%, SkyWest gets 15%, Delta gets 10%), which might be the reason for the increased importance of airline effect.
Results – Feature Importance

<table>
<thead>
<tr>
<th>Feature Category</th>
<th>IAH $\rightarrow$ BOS</th>
<th>BOS $\rightarrow$ IAH</th>
<th>FLL $\rightarrow$ JFK</th>
<th>JFK $\rightarrow$ FLL</th>
<th>LAX $\rightarrow$ SEA</th>
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<td>4</td>
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</table>
Conclusions

• We trained classifiers to predict flight route choice based on highly descriptive features – wind, weather and MITs.
• For most pairs, random forest has the best performance in terms of F1 scores, while gradient boosting has slightly better predictability for IAH → BOS.
• Thunderstorm, wind, rain and MIT are the most important features for most pairs, and the rank of feature importance is largely consistent across airport pairs.
Highlights of the Approach

• Trajectory clustering
  – Large amount of flights $\rightarrow$ small set of clusters.

• Dimension reduction
  – High dimensionality of full feature space $\rightarrow$ small but representative feature space.

• Importance of features
  – Rank consistency.
Ongoing Research

- Improving prediction accuracy
  - High-fidelity convective weather data from NCWF
  - More features to add
    - Special Use Airspace (SUA)
    - Monitor Alert (MA)
    - Airspace Flow Program (AFP)
Ongoing Research

• Improving prediction accuracy
  – High-fidelity convective weather data from NCWF
  – More features to add
    • Special Use Airspace (SUA)
    • Monitor Alert (MA)
    • Airspace Flow Program (AFP)

• Individual flight trajectory prediction tool
  – Multilayer mixture density LSTM network
Thank you!

Q&A

Yulin Liu
liuyulin101@Berkeley.edu
Backup Slides
Overview

• Applying trajectory clustering algorithm to raw trajectory data for selected OD pairs to construct choice set.

• Match flight tracks with different factors such as convective weather, wind and miles-in-trail (MIT) to construct feature space.

• Predict cluster assignment for every flight and understand how different factors affect the assignment results.
Ongoing Research (cont.)

• Individual flight trajectory prediction tool
  – Objectives: given departure time and airspace condition (e.g., weather), or given part of realized flight tracks, what is the expected full actual flight trajectory.
  – Tools
    • Feature engineering: Convolutional Neural Network (CNN).
    • Trajectory prediction: Long Short-Term Memory Network (LSTM).
  – Highlights
    • Capable of incorporating regional features.
    • Account for en route uncertainties.
Ongoing Research (cont.)

- $y_{t-1}$: Gaussian mixtures of $P(Lat, Lon, Alt)$
- $h_{t-1}$: Hidden state
- $x_{t-1}$: $(Lat, Lon, Alt)$
- $c_{t-1}$: Feature vector
Ongoing Research (cont.)

Data Generation

- Wind Data
- Data Cube
- CNN

Diagram:

[Diagram showing relationships between Y, H, X, and C with data generation process]
Ongoing Research (cont.)

Feature Extracted from CNN
Background – Flight Planning System (I)

• Strategic decision making
  – Flight scheduling and route planning prior to departure.

Source: www.skyvector.com
Background – Flight Planning System (II)

• Tactical decision making
  – Adjustments to routes in response to weather or traffic.
  – Example of “Dynamic Weather Route”.

Source: https://www.aviationsystems.arc.nasa.gov/research/strategic/dwr.shtml