Causal Demand Modelling for Applications in En Route Air Traffic Management

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Background

- **Main Goal**
  - To *predict airspace demand* changes that result from TMIs – AFP, CTOP, MIT

- **Types of changes**
  - Demand changes are the result of structured *reroutes, cancellations, substitutions*

- **Importance**
  - By being able to accurately predict demand changes we might be able to *improve TMI planning*
Example

- Rectangular Airspace Sectors
- Yellow sectors – flow control by TMI
- Flights that cross TMI sectors receive arrival slots and departure delay
- Each flight has an option to reroute out of TMI
- Depending on which flights reroute demand patterns may be very different
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- **TMI to learn from**
  - **Airspace Flow Program (AFP)**
    - Controlled Sectors – **Flow Constrained Areas (FCA)**
    - Flights are allowed to reroute outside of FCA
    - Can predict demand based on route choices made in the past

- **Future TMI**
  - **Collaborative Trajectory Options Program (CTOP)**
    - Airlines submit route preference packages – **Trajectory Option Sets (TOS)**
    - Route preferences expressed as **Relative Trajectory Cost**
    - We want to be able to predict routes and route preferences in advance
Background - Model

- Black-box Machine Learning Approaches
- Black-box statistical models are ineffective:
  - Data is extremely highly-dimensional – multiple moving parts, interactions in TMIs
  - Little data relative to data dimensionality
  - TMIs are non-ergodic, unlike coin tosses
    - Seeing one TMI does not tell us everything we need to know about all TMIs
    - Need structural causal TMI model
Background - Model

- **Solution**
  that we investigate
  
  - One solution is to develop a structured economic model **of airline behavior**
  
  - Theory-based model is causal
    - Causal models give us results of **interventions** on variables
    - Example: **change in probability of rerouting** as a result of **increase** in assigned departure **delay**

- **Focus**
  
  - We focus on **predicting reroutes**, that result from AFP/CTOP interventions – ground delay
  
  - Our results can be applied to other TMI-related airline decisions
Background - Model

- **Main Reroute Cost** Parameter

- **Cost Ratio** - \( \frac{\text{Cost of Air Delay}}{\text{Cost of Ground Delay}} \)
  - High Cost Ratio – low willingness to reroute
  - Low Cost Ratio – low willingness to accept departure delay

- **CTOP**
  - Tied to **Relative Trajectory Cost** of structured reroutes in **Collaborative Trajectory Options Program - CTOP**
Research Objective

• General Assumption
  \[ \frac{\text{Cost of Airborne Delay}}{\text{Cost of Ground Delay}} = 2 \text{ or } 3 \]
  • Determined based on accounting of direct costs of reroutes and ground delay

• Main idea
  • To measure cost ratio directly, using observations of decisions made by airlines
    • Recover a function that assigns cost ratio to a given flight

• Reason
  • Cost Ratio may differ based on factors that are not observed directly
Data – Previous Research

- **Number of Observations**
  - >13,000 flights over ~25 days
  - All 13,000 flights are controlled by Airspace Flow Program

- **AFP Option #1** → Choose initial shorter route and get (significant) ground delay

- **AFP Option #2** → Fly a longer route that avoids airspace constraint, get 0 minutes of ground delay
Example Flight From ORD to JFK

Initial route
- Flight Time: 108 minutes
- Ground Delay: 60 minutes

Flow Constrained Area – Region Of Severe Weather that Restricts Airspace Capacity

Reroute
- Flight Time: 130 minutes
- Ground Delay: 0 minutes

ORD to JFK
General Methodology

• **Random Utility Model**

  - Random Utility Models
  - Utility of Route Option = $\alpha \ast \text{Flight Time} + \beta \ast \text{Ground Delay} + \text{other factors} + \text{unobserved factors}$

• **Decision Variable**

  - Decision variable $Y = \{0,1\} – 0$ if flight did not reroute, $1$ if rerouted
    - $Y = 1$ means that utility of option $1$ is higher than utility of option $0$

• **Cost Ratio**

  - Ratio $\frac{\alpha}{\beta}$ is the Cost Ratio we are looking for
  - Initial hypothesis – ratio should be between 2 and 3
Results

• Each airline has a different cost ratio
• Estimated Cost ratios vary significantly

  • Smallest cost ratio – 5:1
  • Largest – over 300:1

Non-parametric Latent Class Logit Model – Vij, Krueger, 2018

→ Many flights reroute for this airline
→ Almost all flights choose shortest path option
Results

• Small Airlines - low cost ratio - many reroutes
• Large carriers – high cost ratios – few reroutes
• Average cost ratios greater than expected – 25:1 vs 3:1 or 2:1

We expected the opposite – many reroutes for large carriers, few for small carriers
Results - Prediction

- Model prediction – poor
- Many false reroutes predicted
- Many real reroutes were misclassified
- Only 310 out of 1416 reroutes were classified correctly
- Advanced machine learning methods do not perform consistently better

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<tr>
<th>Predicted</th>
<th>Actual</th>
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<tr>
<td></td>
<td>1173</td>
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<tr>
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<td>11848</td>
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- Accuracy: 0.82
- Sensitivity: 0.22
- Specificity: 0.9

Confusion Table of the Logit Model. Rows - predicted outcomes, columns - actual outcomes
Explanation: Strategic Actions by Airlines

- Airlines do not control flights myopically
- After rerouting a flight airlines retain its slot and can move other flight to earlier time
- In Random Utility Models we assume that all flights act independently

→ They can optimize aggregate outcome across all flights
→ This may improve total outcome for airline operations
→ Our estimates mind be skewed
Explanation: Strategic Actions by Airlines

- **Demand Curve** represents scheduled demand for a given airline.
- **Departure Curve** represents slots that belong to the airline.
- \( N_{ex} \) is the maximum number of flights that need to be rerouted or cancelled to reduce delay to zero.
- Hypothesis: this fact is responsible for biasing Cost Ratio estimates.

\[ N_{ex} \text{ Excess Accumulation} = \text{Required # Of Reroutes} \]
Simulation of Airline Response

• We devised a very simple optimization model for airline decision making in context of Air Traffic Management
• We use simple simulated data
• 600 flights per simulation, 10 simulations, 6000 flights total.
• We vary number of flights per airline between 1 and 600—all airlines are the same size
Optimization Model

• All flights for each airline have the following information:
  • Initial arrival time at airspace constraint
  • Slot – initial arrival time + required ground delay
  • Shortest path option
  • Reroute option

• Airlines are allowed to perform three actions on each flight:
  • Do nothing
  • Reroute aircraft – get air delay, but save on ground delay
  • Move to another slot
Optimization Model

\[
\min \sum_i \sum_t \left[ a_t x_{it} - s_i (1 - y_i) + r_i \ast y_i \right]
\]

s.t. \[
\sum_t a_t x_{it} \geq s_i (1 - y_i)
\]

\[
\sum_t a_t x_{it} - s_i (1 - y_i) \leq T_{\text{max}}
\]

\[
\sum_t x_{it} + y_i = 1
\]

\[
\sum_{it} x_{it} \leq 1
\]

\[
x_{it}, y_i \in \mathbb{B}
\]

One IP per airline

\(i\) — number of slots per airline

\(i\) varies from 1 to 600

\[
\frac{r_i}{\text{airdel}} = \text{cost ratio}
\]

Cost ratio is provided by us

We are trying to “guess” what the cost ratio really is based on optimization output
Estimation Results for Simulated Schedules

• We varied average number of slots per airline between 600 and 1 – x axis
• We also varied the assumed cost ratio and set it to 2:1, 3:1, and 5:1
• The smaller the number of slots per airline, the closer the estimated cost ratio to the assumed ‘true’ value
Aggregate Estimate

• Issue with Random Utility Estimates

• Solution

• Even in abstract scenarios we can’t estimate cost ratio for airlines with many slots in TMI

• If we add cancellations things only get worse

• Airlines maximize aggregate gain – minimize total delay

• Total Delay Reduction in Minutes ≥ Cost Ratio × Total Air Delay

• Cost Ratio ≤ (Reduction in Delay) / Total Air Delay
Aggregate Estimate

• Aggregate estimates converge faster than random utility estimates
• For airlines with 10 slots we might be able to compute the cost ratio
• This assumes that all delay savings in the aggregate are from reroutes, not cancellations
Practical Limitations of Aggregate Estimation

- Dots – GDP slots (EWR, may 2, 2012), arrows flights moving from one slot to another
- Most slot transfers – **inter-airline slot swaps**
- United Airlines gets slots that belong to Express Jet flights
- United Airlines cancel 1 flight, Express Jet – 4 flights
- Delay **increases** for Express Jet as a result, **decreases** for United Airlines
- For United and Express Jet combined, 1 cancellation on average corresponded to 100 minutes in delay reduction
Practical Limitations of Aggregate Estimation

• **AFP – even more complexity** than GDP
• 3 AFPs interact on July 15, 2012
• ~1,300 flights, ~100 reroutes, ~50 cancellations
• Two revisions – significant changes in delays
• Flights move between all three AFPs
• **Hard to disentangle** cost reductions from cancellations, reroutes, swaps
• In GDP and AFP **decisions are not made simultaneously, but iteratively**, slot movement does not stop at any point
Possible AFP(GDP) Decision Making Heuristic

• **Step 1**
  • Determine the number of reroutes necessary to reduce departure delays for the remaining flights to a minimum - $N_{ex}$

• **Step 2**
  • Select a subset of flights with the lowest reroute cost

• **Step 3**
  • Out of this subset of flights, reroute $N_{ex}$ flights evenly

• **Step 4**
  • Move remaining flights to available earlier slots
Evidence

- July 19, 2012 AFP
- Red line – **0 minutes** of arrival delay if flight chooses to reroute from AFP
- All rerouted flights have **low reroute cost** – in case of reroute most arrive 0 to 50 minutes early
- Overall departure **delay goes down** from 63 to 32 minutes
Conclusions

• Main Conclusion
  • Airlines optimize aggregate outcomes in TMIs, not outcomes for individual flights
  • Interactions between flights **obscure** reroute, cancellation **costs** from us to a large degree
  • This makes it **difficult to build causal**, predictive models of airline behavior
  • **Not only** applies to **random utility models** – any model that attempts to estimate probability of some TMI decision given flight, TMI attributes
    • **Most Machine Learning models**
Conclusions

- Predicting Aggregate Outcomes
  - Models of aggregate outcomes **perform somewhat better**
  - Can hypothetically get estimates of reroute, cancellations costs
  - **Hard** to do in practice

- **CTOP**
  - Modelling airline decisions in Collaborative Trajectory Options Program might be easier
  - Rerouting, cancellations and swaps are **separated** in CTOP
  - **Reroutes are assigned** by command center based on airline preferences
  - Demand prediction achieves **reasonable accuracy**
Thank you!
Collaborative Trajectory Options Program

- Collaborative Trajectory Options Program – CTOP
- Attempts to eliminate disadvantages of AFP
- At the start of CTOP flights submit lists of potential reroutes
  - Trajectory Option Sets
- Without knowing Flow Constrained Areas and capacity rates
- CTOP collects TOSs, orders flight according to a pre-specified rule
  - Not necessarily FIFO, because we might have multiple resources
- Assigns reroutes and delay to flights to re-distribute demand
Example – 2 FCA, 1 Flight, 3 Routes in TOS

Current Trajectory:
RO1 ETD 14:00z
RO3 ETD 14:00z

Flight controlled out of FCA001
Example – same Routes, different RTC

Current Trajectory:
RO3 ETD 15:00z

RO1 (0)
RO2 (15)
RO3 (40)

<table>
<thead>
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<th>ERTD</th>
<th>RO</th>
<th>RTC</th>
<th>RMNT</th>
<th>TVST</th>
<th>TVET</th>
<th>Delay Required</th>
<th>Adj. Cost</th>
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<td>15:00</td>
<td>RO1</td>
<td>0</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>45</td>
<td>45+0=45</td>
</tr>
<tr>
<td>15:00</td>
<td>RO2</td>
<td>15</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>30</td>
<td>30+15=45</td>
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<tr>
<td>15:00</td>
<td>RO3</td>
<td>40</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>0</td>
<td>0+40=40</td>
</tr>
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Data for TOS Prediction

- CTOP data is produced by the Simulation Engine
- Mimics SWIM data that will be available in real-life situations
- 10,000 flights
- 5 FCAs
- 8 simulation runs with different capacity levels
- 300-1000 reroutes per simulation
Data for TOS Prediction

- Key parameter of TOS prediction is RTC
  - Set of available routes is known to us
  - By predicting RTC values for reroutes we can predict TOS
- We assume that \( RTC = \text{Cost Ratio} \times \Delta \text{Flight Time} + \text{other factors} \)
- Main task – estimate \textbf{Cost Ratio} from data
- Potential reroutes and \( \Delta \text{Flight Time} \) for them is known
- As a result, RTC for each potential reroute can be predicted if we know the \textbf{Cost Ratio}
Data for TOS Prediction

• 1 FCA
• We observe flight from ORD to JFK
• We observe the reroute because CTOP assigned the reroute to this flight
Data for TOS Prediction

- 1 FCA
- Same O-D pair, but flight was assigned direct route
- We cannot infer RTC directly
- Need to impute the alternative routes using simulation engine
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Random Utility Model

- Builds on the work done in Year 1 and Year 2 using AFP data
- We attempted to estimate RTC for AFP flights using observed reroutes
  - Estimates of RTC were highly biased
  - Cause of bias: airlines coordinate actions between individual flights
  - Flight coordination distorts parameter estimates
- CTOP resource allocation eliminates this issue
  - For CTOP data we can reliably estimate parameters
Utility Function of CTOP Route Options

• CTOP assigns route from two alternatives: shortest path and reroute
  • Flight Time, Delay, Connections, O-D pair
    • \( U_{\text{Route}} = RTC_{\text{Route}} + \text{Ground Delay}_{\text{Route}} \)
  • For the shortest route option the RTC value is equal to zero:
    • \( U_{\text{Shortest}} = 0 + \text{Ground Delay}_{\text{Shortest}} \)
  • For the second TOS option:
    • \( U_{\text{Reroute}} = RTC_{\text{Reroute}} + \text{Ground Delay}_{\text{Reroute}} \)
  • Or alternatively:
    • \( U_{\text{Reroute}} = (\text{Cost Ratio} \times \Delta \text{Flight Time}_{\text{Reroute}} + \epsilon) + \text{Ground Delay}_{\text{Reroute}} \)
  • If we observe international connections:
    • \( U_{\text{Reroute}} = (\text{Cost Ratio} \times \Delta \text{Flight Time}_{\text{Reroute}} + \beta \times \text{Int. Connection} + \epsilon) + \text{Ground Delay}_{\text{Reroute}} \)
Utility Function of CTOP Route Options

\[ U_{\text{Reroute}} = (\text{Cost Ratio} \times \Delta \text{Flight Time}_{\text{Reroute}} + \beta \times \text{Int. Connection} + \epsilon) + \text{Ground Delay}_{\text{Reroute}} \]

- **Cost Ratio**, \( \beta \) can be estimated using standard logistic regression
  - Alternatively, we can use more complex, fine-grained models that we developed

- Ground delay coefficient should be equal to 1

- If flight time is the only determinant of RTC, constant term in this model should be equal to zero
Estimation Results

- Here, airlines have varied Cost Ratio values
- Ground Delay coefficient is close to 1
- Constant term is zero
- Airlines have different Cost Ratio values
- 95% Confidence interval of Cost Ratio for AAL:
  - Cost Ratio = $2.3 \pm 0.27 \times 1.96$
- $R^2 = 0.73$

| Flight Time | Estimate | Std. Error | z-value | Pr(>|z|) | RTC |
|-------------|----------|------------|---------|----------|-----|
| Constant Term | -0.09 | 0.18 | -0.53 | 0.5944 |     |
| AAL         | -2.30 | 0.27 | -8.37 | 2.20E-16 | 2.29 |
| DAL         | -2.05 | 0.22 | -9.02 | 2.20E-16 | 2.04 |
| EDV         | -1.67 | 0.32 | -5.14 | 2.67E-07 | 1.66 |
| ENY         | -1.89 | 0.46 | -4.06 | 4.73E-05 | 1.88 |
| JBU         | -1.87 | 0.37 | -4.99 | 5.75E-07 | 1.86 |
| NKS         | -1.92 | 0.33 | -5.73 | 9.49E-09 | 1.91 |
| SWA         | -1.68 | 0.18 | -8.90 | 2.20E-16 | 1.67 |
| UAL         | -2.27 | 0.30 | -7.43 | 1.07E-13 | 2.26 |
| Delay       | -1.005 | 0.10 | -10.01 | 2.20E-16 |     |
Connecting Stochastic TOS Generation to Predict CTOP Demand Profile

- Goal: use estimated TOS parameters to create aggregate predictions of demand on key resources
- Run Monte Carlo simulation:

  - For every flight, random draw of TOS
  - Run CTOP resource allocation (CRRAT)
  - Analyze demand on resources

  Repeat 1000s of times

  Ensemble forecast of demand on key resources
Learning Reroute Costs in CTOP

- We used learned **Cost Ratios** for different airlines to predict FCA demand profile for a different simulated CTOP
- **2 FCAs** – capacity is 15, 25, 35 flights per 15 minutes per FCA for 3 scenarios
- Scheduled demand – 36 flights per 15 minutes
- We **run Monte Carlo** simulation to get forecasted demand distribution
- **Accuracy for individual flights is much higher** than for AFP reroute prediction
- Aggregate demand for FCAs is predicted almost **without error**

<table>
<thead>
<tr>
<th></th>
<th>Cap = 15</th>
<th>Cap = 25</th>
<th>Cap = 35</th>
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<tbody>
<tr>
<td><strong>RMSE</strong></td>
<td>1.22</td>
<td>2.05</td>
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<tr>
<td><strong>Mean Demand</strong></td>
<td>5.00</td>
<td>8.33</td>
<td>11.05</td>
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<tr>
<td><strong>Error % of Mean</strong></td>
<td>24%</td>
<td>25%</td>
<td>9%</td>
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