FORCES
FOUNDATIONS OF RESILIENT CYBER-PHYSICAL SYSTEMS

Data-Driven Modeling of Human Decision Making Processes

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Introduction

Motivation

* Many systems require significant interactions of automation with human decision makers
* Objective functions can descried these decision processes
  - Used to optimize system wide performance
  - Used to develop decision support tools

Presentation Outline

1. Discrete choice modeling approach
2. Case study for DCM at LaGuardia Airport in New York
   - Estimation of objective functions
   - Using objective functions for prediction

Discrete Choice Framework

Decision Maker:
Air Traffic Controller

Choice Set of Alternatives

Runway Config. A | Runway Config. B | Runway Config. C

Each choice has a utility

Utility A | Utility B | Utility C

Utility is a function of attributes

U_A (wind, demand, …) | U_B (wind, demand, …) | U_C (wind, demand, …)

The Random Utility Model

- DCM uses The Random Utility Model
  - Utility of choice $c_i \in C_n$ for the n^{th} decision maker:

$$U_{i,n} = V_{i,n} + \varepsilon_{i,n}$$

Observable Component

Random Error Component

- **Observable Component:**
  - Linear function of attributes: $V_{i,n} = \alpha_i + \sum[\beta_i \cdot X_{i,n}]$
  - $\hat{\alpha}, \hat{\beta}$ estimated via MLE

- **Random Error Component:** captures all forms of model error (measurement errors, unobserved attributes, proxy variables, etc.)
  - Probit model: Gaussian error term
  - Logit model: Extreme value error term

Logit Models

Logistic Probability Un**it**

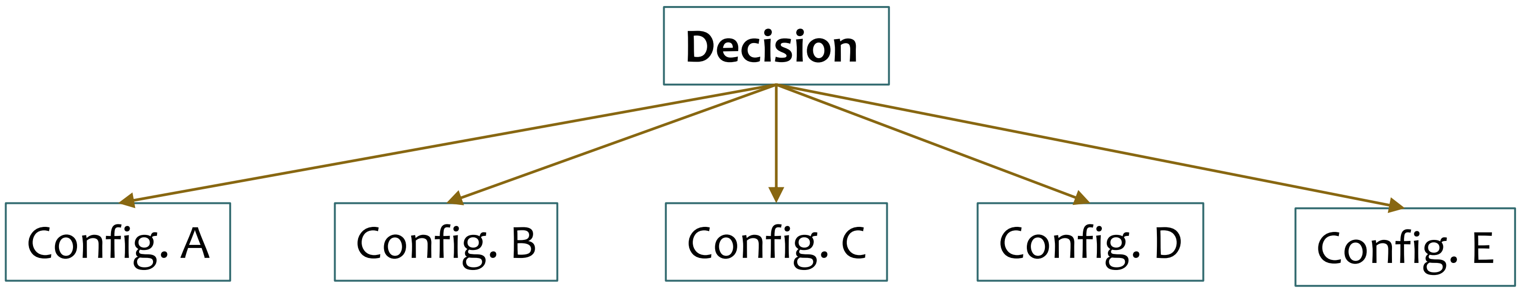
Logit

- Logit is more computationally tractable than Probit models
  1. Has a closed form solution
  2. Especially important as models get more complicated
  3. Approximates the normal distribution well (fatter tails)

- Specifically, we use a Gumbel distribution for error term with η=0

$$f(x) = \mu \exp\big(-\mu(x-\eta)\big) \cdot \exp\big(-\exp\big(\mu(x-\eta)\big)\big)$$

Multinomial Logit Model



- Now choice set, C_n, has J_n multiple alternatives.

- All error terms, ϵ_{jn} are independent and identically distributed (i.i.d.)

$$f(\epsilon) = \mu \exp(-\mu\epsilon) \cdot \exp(-\exp(\mu\epsilon))$$

- Closed form solution for probability

$$P(i|C_n) = \frac{\exp(\mu V_{i,n})}{\sum_{j\in C_n}[\exp(\mu V_{j,n})]}$$

Multinomial Logit Model: IIA

- Independence of Irrelevant Alternatives (IIA)
- i.i.d. error terms

$$P(i|C_n) = \frac{\exp(\mu V_{i,n})}{\sum_{j \in C_n}[\exp(\mu V_{j,n})]}$$

$$\frac{P(i|C_1)}{P(j|C_1)} = \frac{P(i|C_2)}{P(j|C_2)} \qquad \forall \begin{cases} i, j \in C_1 \\ i, j \in C_1 \\ C_1 \subseteq C_n \\ C_2 \subseteq C_n \end{cases}$$

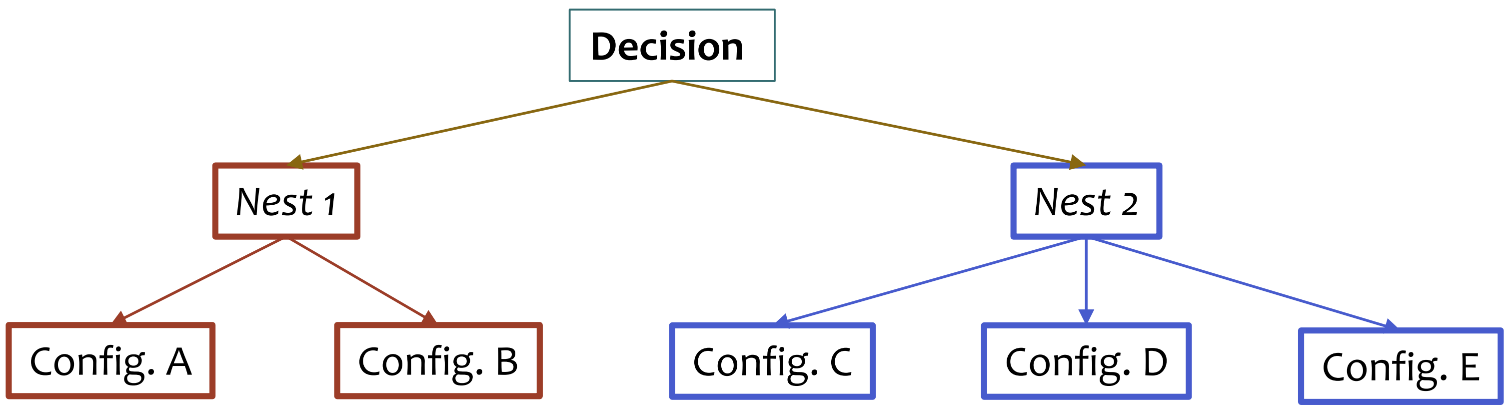
Main Takeaway:
The ratio of choice probabilities for alternative i and j does not depend on the characteristics of the other alternatives

- IIA assumption can be restrictive
  - Assumes that none of the categories can serve as substitutes
  - Can produce inaccurate results
  - Fails when alternatives are correlated

Nested Logit Model Structure

Q: How do we overcome problems when alternative are correlated?

A: Split model into a tree structure that allows correlation within "Nests"



- Between nests choices for i and j are independent
- Alternatives within nests are now correlated

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Nested Logit Model Mathematics

* Error terms, $\epsilon_{j,n}$ now have the following joint cumulative distribution

$$F(\epsilon_{1,n}\,, \epsilon_{1,n}, \dots\,, \epsilon_{J,n}) = \exp\left(-\sum_{s=1}^{S}\left[\left(\sum_{j\in B_s}\left[\exp\left(-\frac{\epsilon_{j,n}}{\mu_s}\right)\right]\right)^{\mu_s}\right]\right)$$

* NL probabilities can be expressed as the product of two simple Logits using conditional probabilities.

$$P_n(i) = P_n(i|B_k)P_C(B_k)$$

$$\text{where } B_k \text{ is the } k^{th} \text{ nest}$$

* NL formulation will have three components
  1. Lower model
  2. Upper model
  3. Bridge between levels

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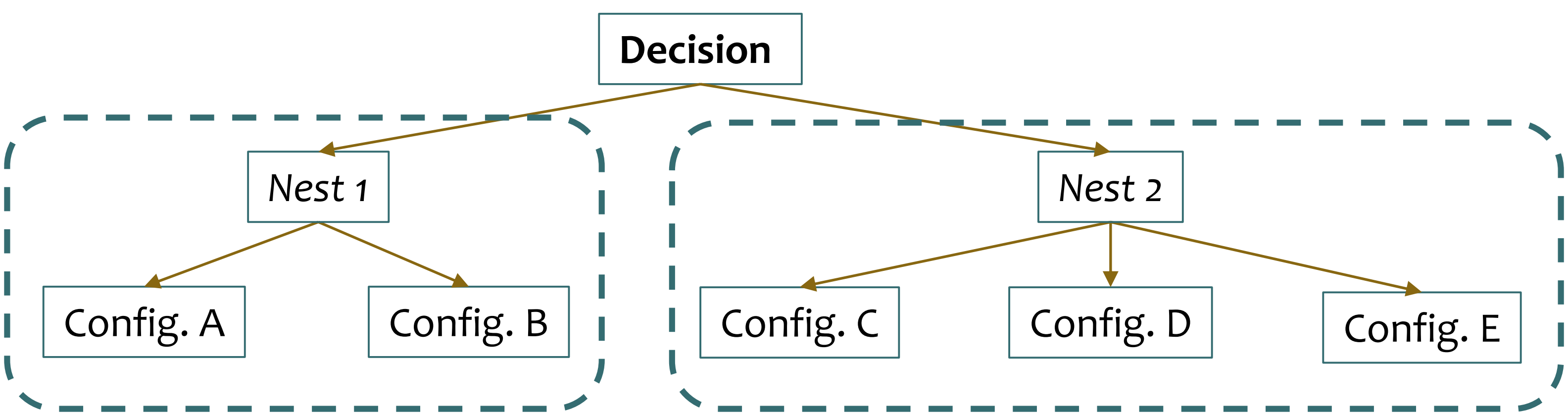
Nested Logit Model Mathematics

Lower Model

* Gives conditional probability of picking an alternative given a nest.
* Each nest is a simple MNL structure

$$P_n(i|B_k) = \frac{\exp(\mu_k V_{i,n})}{\sum_{j \in B_k}[\exp(\mu_k V_{j,n})]}$$



Nested Logit Model Mathematics

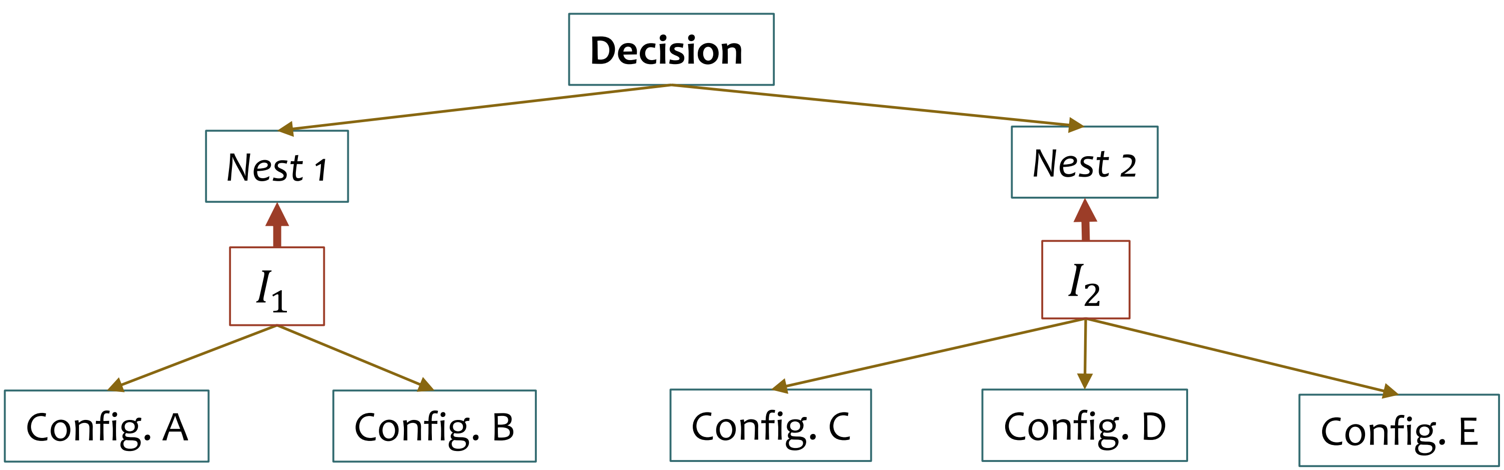
Bridge

Q: The interpretability is great, but how do we link the upper and lower models?

A: Inclusive value (or inclusive utility)

- Inclusive value is the expected maximum utility from each nest
- Carries information from lower model to upper model

$$I_{k,n} = \frac{1}{\mu_k} \ln\left(\sum\nolimits_{j \in B_k} \left[\exp\left(\mu_k V_{i,n}\right)\right]\right)$$

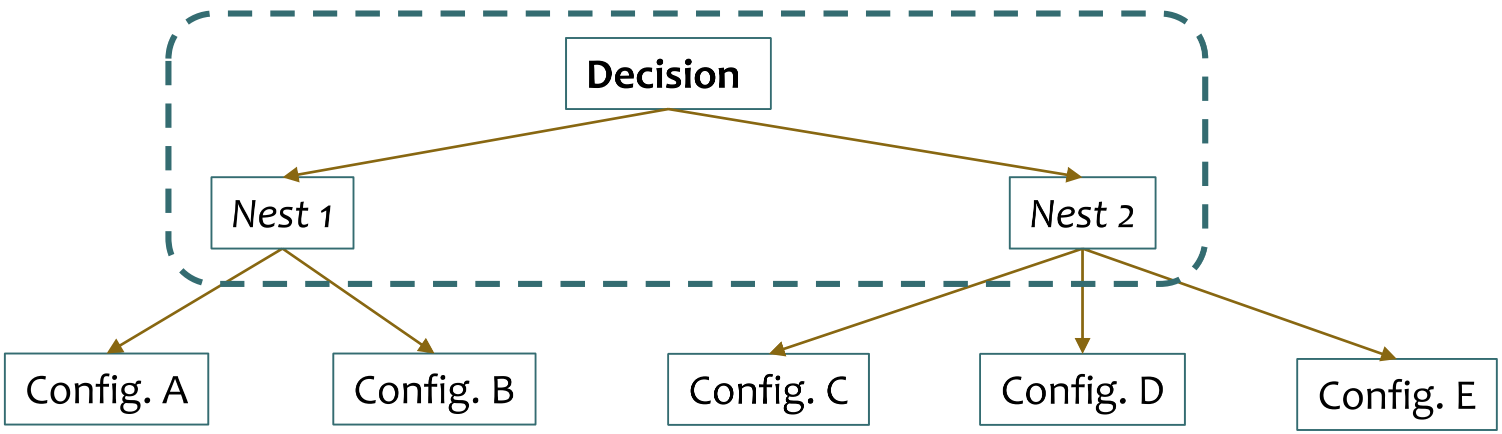


Nested Logit Model Mathematics

Upper Model

* Gives marginal probability of nest choice over all alternatives
* Inclusive value carries information into upper model
* Upper level model is also a simple MNL model

$$P_n(C_k) = \frac{\exp(I_{k,n})}{\sum_{l=1}^{n}[\exp(I_{l,n})]}$$



Other types of DCMs

* Multinomial Probit
* Cross Nested Logit
* GEV Models
* Mixed Logit
* Mixed Probit
* Choice Set Generation

Case Study: LaGuardia Airport

LaGuardia Airport (LGA) in New York

Background:

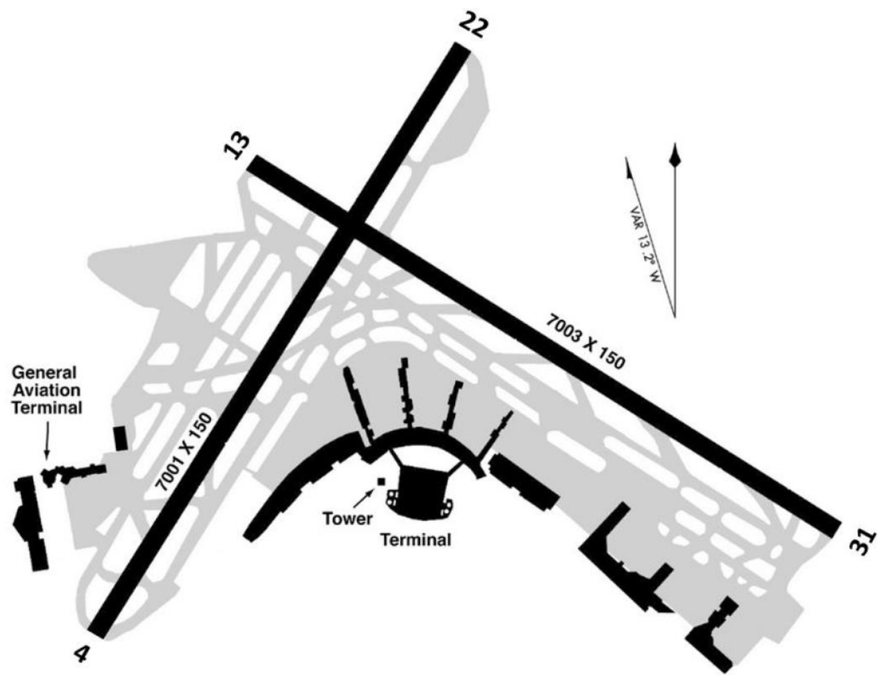
* Airport congestion leads to significant flight delays. The key driver of airport capacity is the runway configuration. Air traffic controllers (ATC) must select the runway configuration at a given time based on a set of operational and meteorological conditions.

Goals:

1. To infer the ATC utility functions for the runway configuration decision selection
2. To predict the runway configuration at a given time, given a forecast of influencing factors

Runway Configuration

LGA



R1, R2 | R3, R4

arrival runways ← R1, R2 | R3, R4 → departure runways

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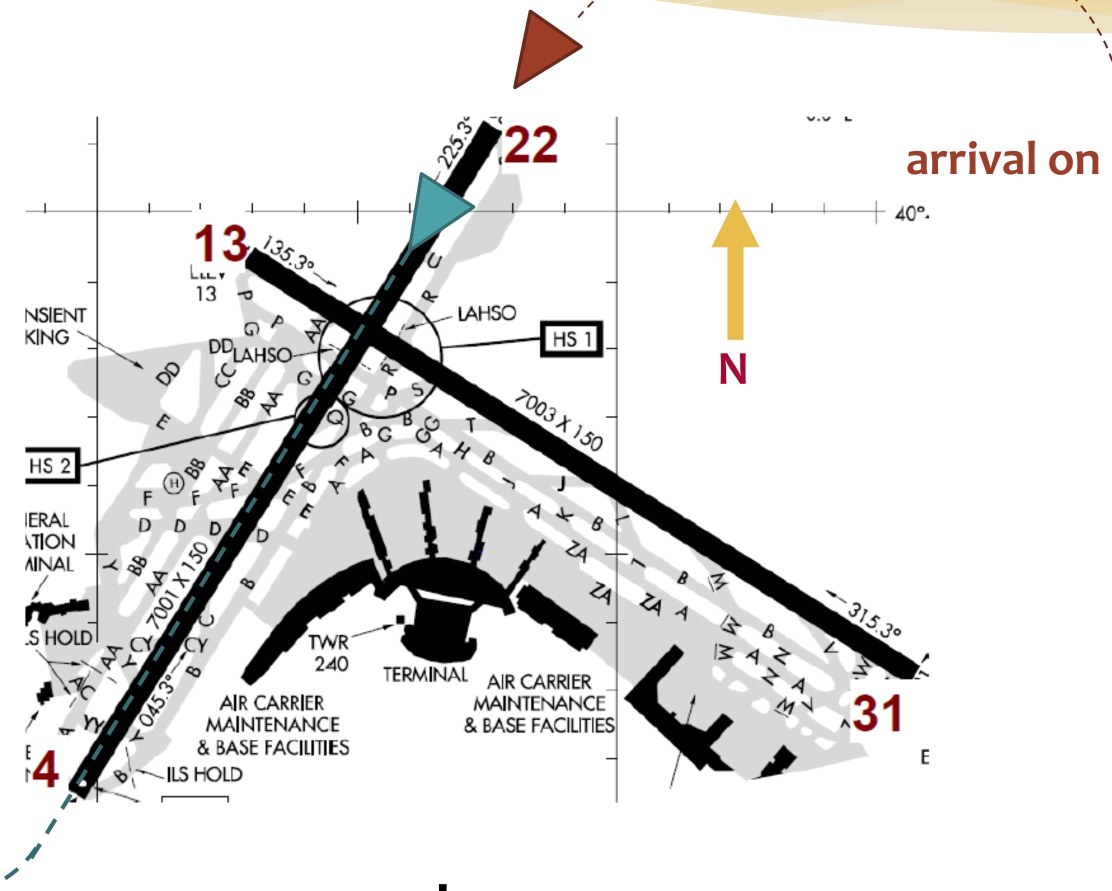
Runway Configuration Example



arrival on runway 22

departure on runway 22

22 | 22

Dataset

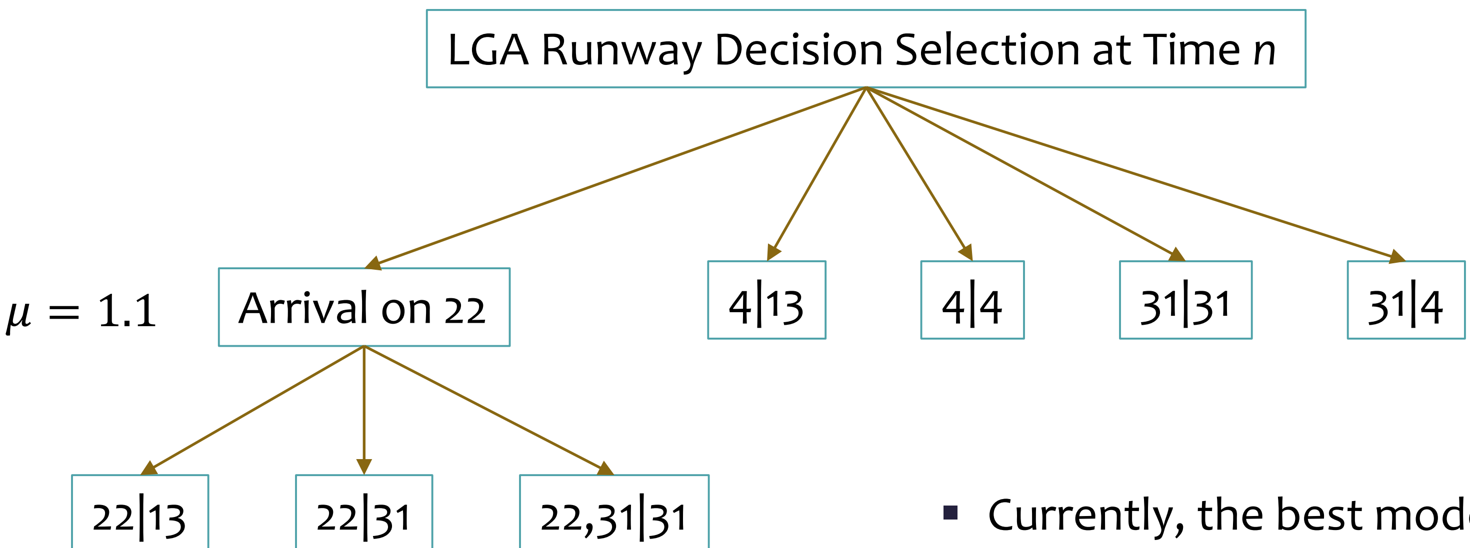
* Datasets were obtained from the FAA Aviation System Performance Metrics (ASPM) database.
* ASPM data reports operational and meteorological data (wind speed, runway configuration, demand, etc.) in 15-minute intervals.
* Model was trained on ASPM data for LGA year 2011.
* Model was tested on ASPM data for LGA year 2012.

Candidate Runway Configurations

- Runway configurations that were reported more than 1% (excluding late evening and early morning hours) in 2011 were considered as candidate runway configurations for the model.
- Resulted in 7 candidate configurations

Configuration	Frequency
31|4	6,772
22|13	5,679
22|31	4,488
4|13	3,325
31|31	1,483
22,31|31	820
4|4	813

NL Model Specification



- Currently, the best model follows a nested logit structure with alternatives that have arrivals on runway 22 grouped into a nest.

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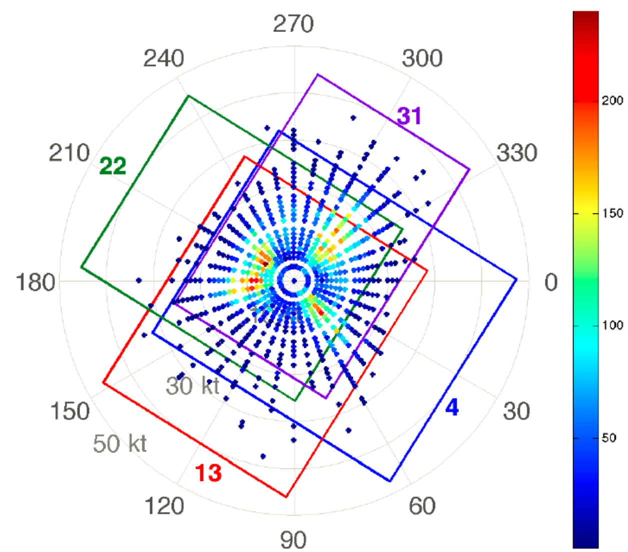
Runway Configuration Selection Dynamics

* Attributes that potentially drive decision processes of air traffic controllers
  1. Wind speed
  2. Wind direction
  3. Visibility
  4. Airport arrival demand
  5. Coordination with surrounding airports
  6. Noise mitigation
  7. Difficulty of switching around airport
  8. Inertia – resistance to configuration switches because of operational difficulties

(1–2) Also affects availability

Wind Rose



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Estimated Utility Function Weights

Parameters	Value	Std. error	t-statistic
Inertia parameters			
Config. 22|13	4.58	0.187	24.5
Config. 22|31	7.41	0.36	20.57
Config. 22,31|31	7.41	0.36	20.57
Config. 31|31	4.91	0.401	12.24
Config. 31|4	3.16	0.25	12.6
Config. 4|13	3.99	0.196	20.34
Config. 4|4	5.44	0.416	13.1
Wind parameters			
High headwind on arrival runway	0.0952	0.0161	5.89
Normal headwind on arrival runway	0.123	0.0197	6.26
Tailwind on arrival runway	-0.0946	0.0199	-4.74
Tailwind on departure runway	-0.211	0.0173	-12.2
Tailwind on extra arrival runway	-0.348	0.07	-4.97

Compression effects

Estimated Utility Function Weights

Parameters	Value	Std. error	t-statistic
Demand parameters			
Arrival demand: 31|31	-0.101	0.0312	-3.24
Arrival demand: 4|4	-0.0807	0.0327	-2.47
VMC/IMC parameters			
VMC on 31|31	2.09	0.402	5.19
VMC on 31|4	1.36	0.231	5.9

- The low capacity runways have negative contributions to the utility based on demand.

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Estimated Utility Function Weights

Parameters	Value	Std. error	t-statistic
Switch proximity parameters			
31|4 to 31|31	-1.4	0.463	-3.03
4|13 to 31|31	-2.52	0.714	-3.53
4|4 to 31|31	-1.32	0.747	-1.77
22|13 to 31|31	-1.99	0.577	-3.45
4|13 to 31|4	-2.19	0.368	-5.94
4|4 to 31|4	-1.05	0.515	-2.04
22|13 to 31|4	-2.14	0.355	-6.04
4|13 to 4|4	-1.6	0.443	-3.61
22|13 to 4|4	-1.92	0.532	-3.6
31|31 to 22|13	-1.05	0.573	-1.84

- Some runway switches are less preferable than others.

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Estimated Utility Function Weights

Parameters	Value	Std. error	t-statistic
Inter-airport coordination parameters			
JFK arr. on 13; LGA arr. 22 / dep. 4	0.85	0.308	2.76
JFK arr. on 13; LGA arr. 31 / dep. 13	1.27	0.464	2.75
JFK dep. on 13; LGA arr. 13 / dep. 31	-1.99	0.224	-8.88
JFK arr. on 13; LGA arr. 4 / dep. 22	-0.448	0.172	-2.6
JFK arr. on 13; LGA arr. 13 / dep. 31	-1.61	0.222	-7.26
JFK arr. on 13; LGA arr. 31 / dep. 13	0.796	0.25	3.19
JFK dep. on 13; LGA arr. 13 / dep. 31	-2.5	0.341	-7.34
JFK arr. on 13; LGA arr. 22 / dep. 4	-0.737	0.293	-2.51
JFK dep. on 13; LGA arr. 4 / dep. 22	-1.15	0.312	-3.68

- Coordination with JFK is an important factor to the decision process
- ATC likes to align arrival and departure flows

Runway Configuration Prediction: 15-min Horizon

Runway Configuration	Frequency	Accuracy
22|13	8,220	98.1%
31|4	6,454	98.4%
4|13	4,851	97.9%
22|31	2,938	97.3%
31|31	2,136	96.8%
22,31|31	1,838	96.7%
4|4	795	96.7%
Total	27,232	95.3%

* Very high accuracy, especially for configurations that were seen frequently throughout the year.

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Runway Configuration Prediction: 3-hr Horizon

Runway Configuration	Frequency	Accuracy
22|13	8,220	89.0%
31|4	6,454	84.8%
4|13	4,851	83.0%
22|31	2,938	71.6%
31|31	2,136	67.0%
22,31|31	1,838	67.2%
4|4	795	68.2%
Total	27,232	82.2%

- Utility functions were used to calculate the probabilities of picking a configuration at each time period.
- Bayes rule was used recursively to forecast on a three-hour time horizon.
- The configuration with the highest probability was taken as the prediction.
- Accuracy declined by about 13%

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3-hr Prediction Using Forecast Data

Runway Configuration	Frequency	Accuracy
22|13	1,096	91.2%
31|4	369	72.1%
4|13	250	73.6%
22|31	186	57.5%
31|31	244	67.6%
22,31|31	69	44.9%
4|4	35	68.6%
Total	2,249	79.0%

- TAF and schedule demand for LGA July 2014
- Accuracy reduced by about 3%, but was not significantly degraded.

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Concluding Remarks

Discrete Choice Models

* Have the power to reduce the objective functions of human decision making processes
* Useful for identifying the biggest influencing factors in the decision making process
* Inherently data-driven
* Difficulty estimating factors that are not represented in the data (as expected)

Prediction with Discrete Choice Models

* Model reaches accuracies upwards of 95% for a 15 minute horizon
* Model reaches accuracies upwards of 80% for a three hour horizon
* Forecast data does not significantly reduce accuracy of prediction
* Accuracies increase with configurations that were seen frequently

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