Data-driven System Simulation in NYGH ED

**Prof. Opher Baron, Prof. Dmitry Krass,
Prof. Arik Senderovich, and Nancy Li**
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01

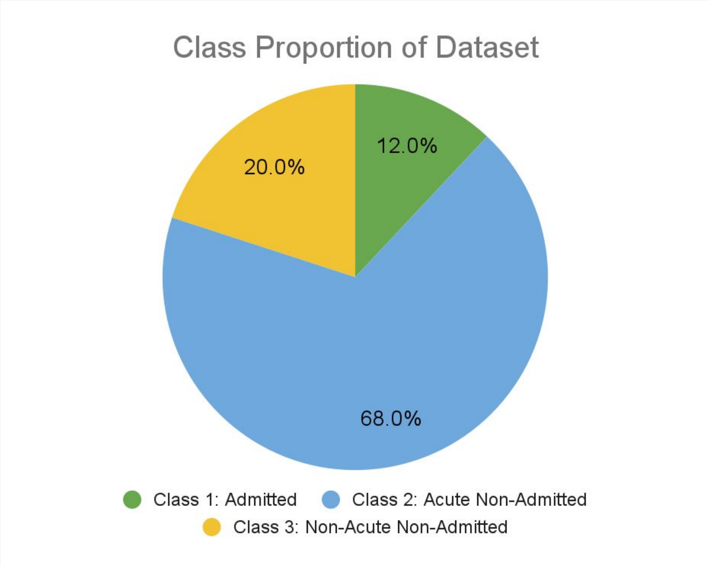
Introduction

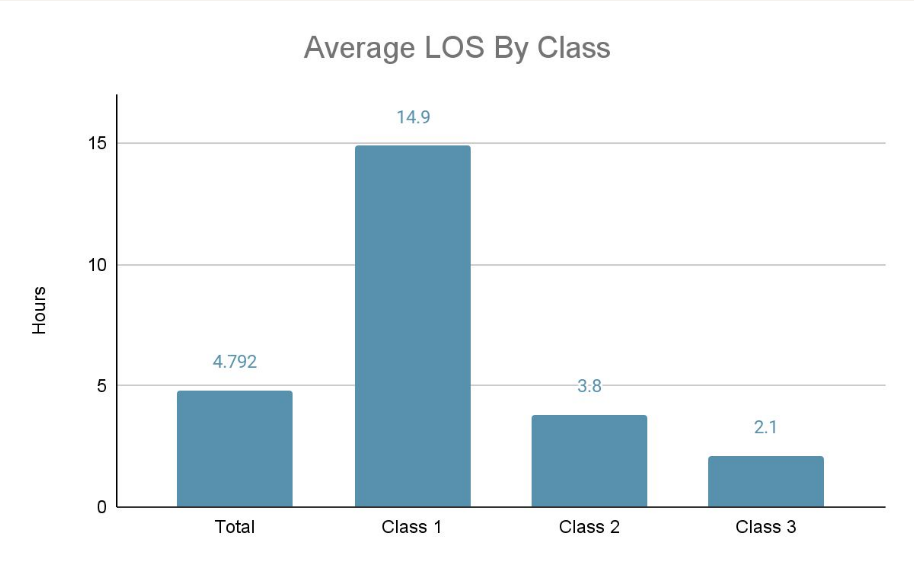
Review of Previous Work

Project Overview

- Project initiated in early 2019
  - Primary goal: identify key drivers of wait times in NYGH ED
  - Hypothesis: long consult times are a key contributor to wait times
- Phase I: Statistical Approach (results presented in late 2019)
  - Identified many significant drivers of wait times
  - Consults lead to large increases in LOS for affected patients
  - However, reduction in consult times would not lead to a large reduction of mean or 90p LOS for non-admitted patients
    - The % of non-admitted patients requiring consults is too small

Data Summary





*Total is a weighted average of the 3 classes

Consult and LOS

- However... consults **do not** significantly impact 90P LOS for Classes 2 and 3 as there are too few consults

- Nearly all Class 1 patients require consults, thus reducing consult times **may** impact 90P LOS of this class

	Class 1	Class 2	Class 3
Consulted Patients (h)	28.6	13.4	9.9
Non-Consulted Patients 90P (h)	26.2	6.4	3.7
LOS 90P (h)	28.5	6.8	3.8
% Difference Non-Consulted vs. Overall LOS	9.2%	5.9%	2.4%

Phase I critique: First and Second-Order Effects

- **First-order effect**: direct effect of long consult times on the patient requiring a consult
- **Second-order effect**: indirect effects on patients not requiring consults
  - Consult patients occupy space in ED for extended periods of time
  - This leads to ED overcrowding
  - Increasing wait times for all other patients
  - Domino effect: patients arriving long after the consult patient is gone are still affected
- Statistical models not well-suited to identify such indirect effects
  - While ED crowding an occupancy measures were identified as drivers of wait times, the indirect effects were not estimated
  - Efforts to extract projections of second-order effects from stat models not successful (Summer of 2020)

Phase II: Data-Driven Simulation Model

- Second-order effects are easy to extract from a simulation model
- However, designing such a model is very time-consuming and data-intensive task
- Many recorded “failures” in HCS settings
- Our approach is “Data-Driven Simulation”
  - Using Machine-Learning to automatically construct a simulation model
  - The model is “state-aware”, where “state” reflects occupancy of ED at any given time
  - The model can then be used to estimate both first and second order effects
- Additions to the research team: Dr Arik Senderovich (PI), Nancy Li (RA)

Key Research Question

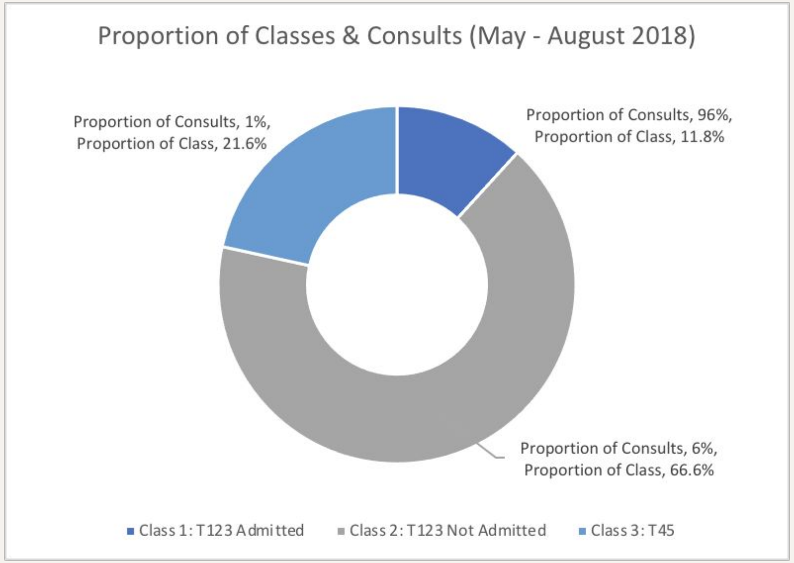
- **What is the expected impact of reducing consult patient's length of stay in the ED by, for example, 50%?**
    - First-order impact: direct reduction of consult times
    - Second-order impact: indirect reduction from decrease in ED Occupancy

02

Analysis Approach

Simulation Model

Data Summary



- **Data Range:** May - August 2018
- **Data Preprocessing:** 39,002 → 38,905 records
- **Patient Classes:**
  - **Class 1 (most consults occur in this class):** Patients with triage codes 1, 2, or 3, admitted to hospital after ED visit
  - **Class 2 (most patients in this class):** Patients with triage codes 1, 2, or 3, not admitted to hospital after ED visit
  - **Class 3:** All patients with triage codes 4 or 5

Automated Data-Driven Simulation Model Pipeline

Tiered Process Map

Pipeline Start

Get User Specification
- Context
- Process abstraction (system state)
- Interventions

Construct ED Model
- Automatically learned from the data
- Apply interventions

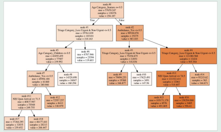
Apply Diagnostics & Analytics
- Diagnostics on goodness of fit
- Intervention impact

Pipeline End

Select System State

Gather All Model Training Features

Train LOS Model
- Random Forest



Simulate + Apply Interventions

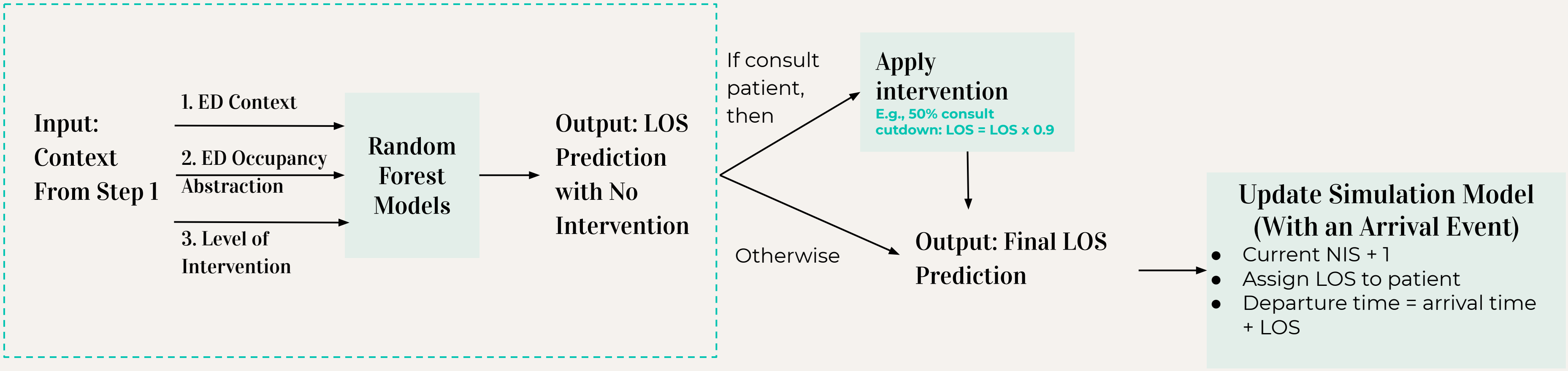
Step 1: Get User Specifications

- **ED Context**
  - **Patient Static Information:** age, gender, ambulance, consult, initial zone, arrival hour, arrival day of week
  - **Season:** arrival week number, arrival month
  - **Trend:** number of weeks since beginning of training data
  - **Holidays:** Ontario public holidays

- **ED Occupancy Abstraction (computed at the beginning of each patient arrival event)**
  - **General NIS (1):** Total **n**umber of patients **i**n the **s**ystem (ED) at the time of arrival
    - ***NIS*** *=* ***N****umber* ***I****n the* ***S****ystem*
  - **NIS by Patient Type (3):** T123 Admitted, T123 Not Admitted, T45
  - **NIS by Zone (11):** e.g., GZ, YZ
  - **NIS by Patient Type x Zone (33)**

- **Level of Interventions**
  - Reduce consult patients' length of stay in the ED by **0% (no intervention), 10%, 20%, 30%, 40%, and 50%**

Step 2: Construct ED Simulation Model

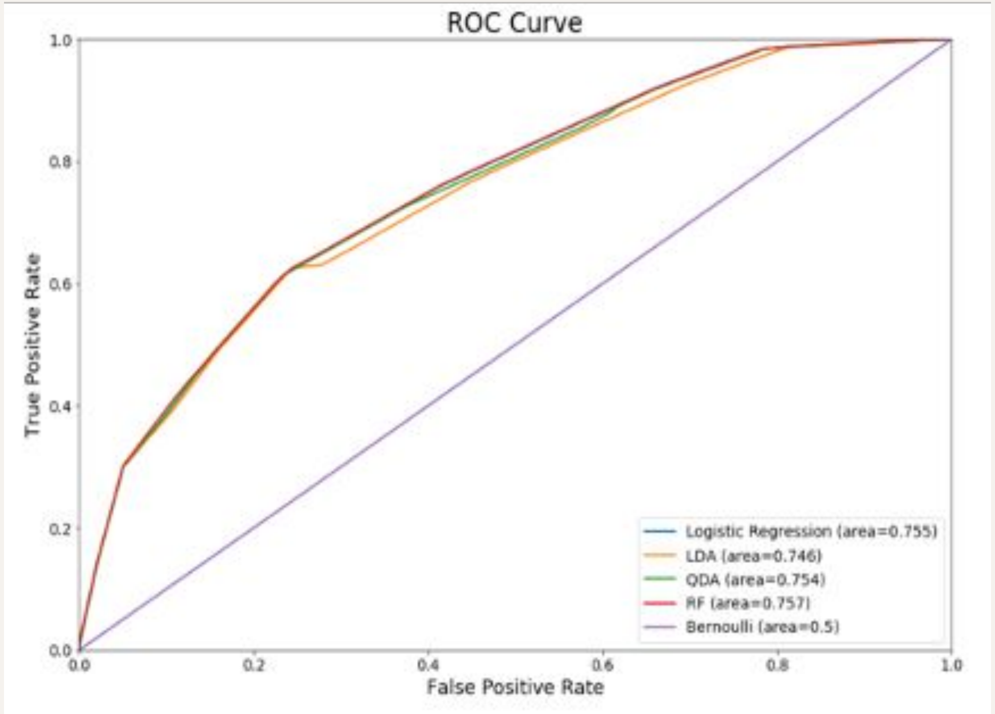


- ***Train Random Forest (RF) Regressor models (a separate model for each NIS type) using training set (May - July 2018)***
- ***Trained RF models are used to sample LOS in test set (August 2018)***

Predicting LOS: Phade II vs Phase I

- LOS Prediction model is at the heart of our approach
- For Phase II
  - Model must be non-anticipative (cannot include information for future arrivals in ED, as well as their LOS)
    - Otherwise cannot use for simulation modeling
  - Requirement was not satisfied by Phase I models (since goals were different)
- Model is “state-aware”, where “state” is represented by NIS
  - Separate model constructed for each NIS type
    - General NIS: 1 model
    - Patient-type NIS: 3 models
    - Etc.

Learning Consult Model - Selection



- Many different Machine Learning modeling forms were tested
    - ROC curve/ AUC is a common way to identify best-performing model
- Best results obtained with Random Forest (RF) predictor
    - Best Model: RF (AUC = 0.757)
- Our approach is model-agnostic: with new data modeling form is adjusted to identify best predictor of LOS

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Results

First- and Second-Order Impacts

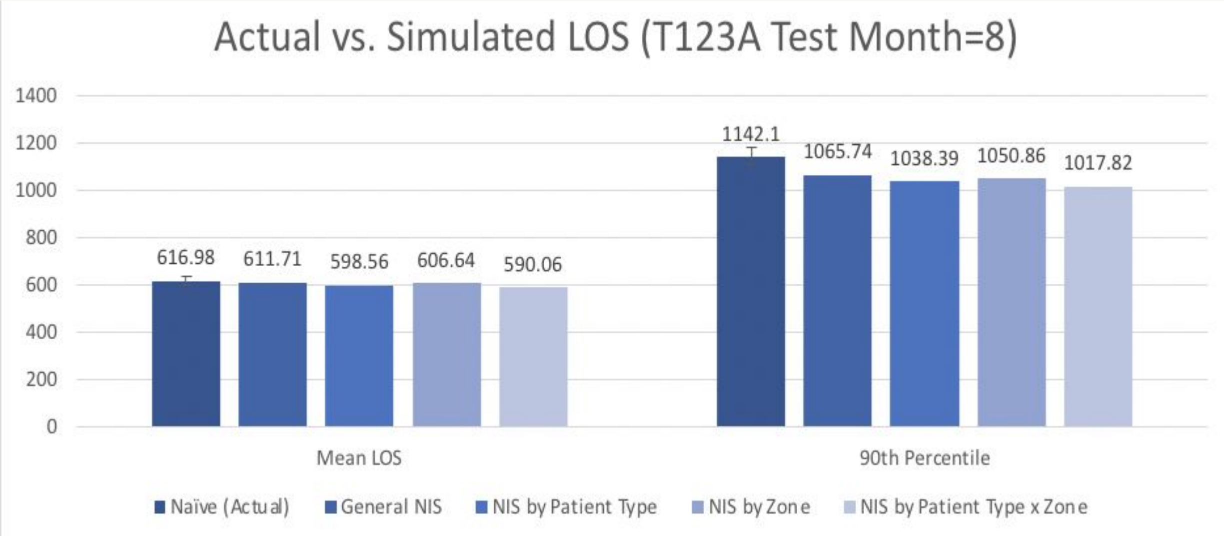
Step 3a: Apply Diagnostics & Analytics

- **Does our prediction model simulate LOS well?**
  - Use model to simulate LOS under “no intervention” conditions
  - Do our models re-create actual system performance?
  - Which NIS type works best?

- **Diagnostics on Goodness of Fit**
  - Comparison of Mean and 90p LOS by NIS type
  - Histograms of LOS and Q-Q Plots (LOS Distributions); Kolmogorov-Smirnov (KS) Test

Actual vs. Simulated LOS, T123 Admitted

Goodness of Fit: Mean & 90th Percentile Predictions (in Minutes)

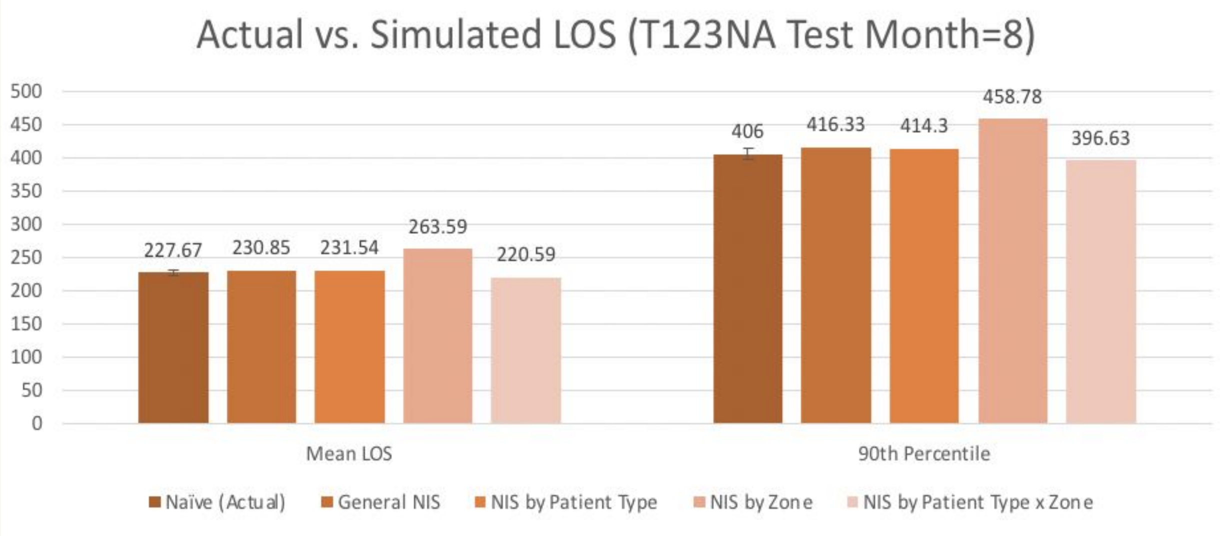


- Models estimate mean LOS well
- Underestimate 90p LOS
- Simpler model (General NIS) does better than more complex ones

Mean 95% CI: (597.82, 636.13)
90th Percentile 95% CI: (1108, 1180)

Actual vs. Simulated LOS, T123 Not Admitted

Goodness of Fit: Mean & 90th Percentile Predictions (in Minutes)

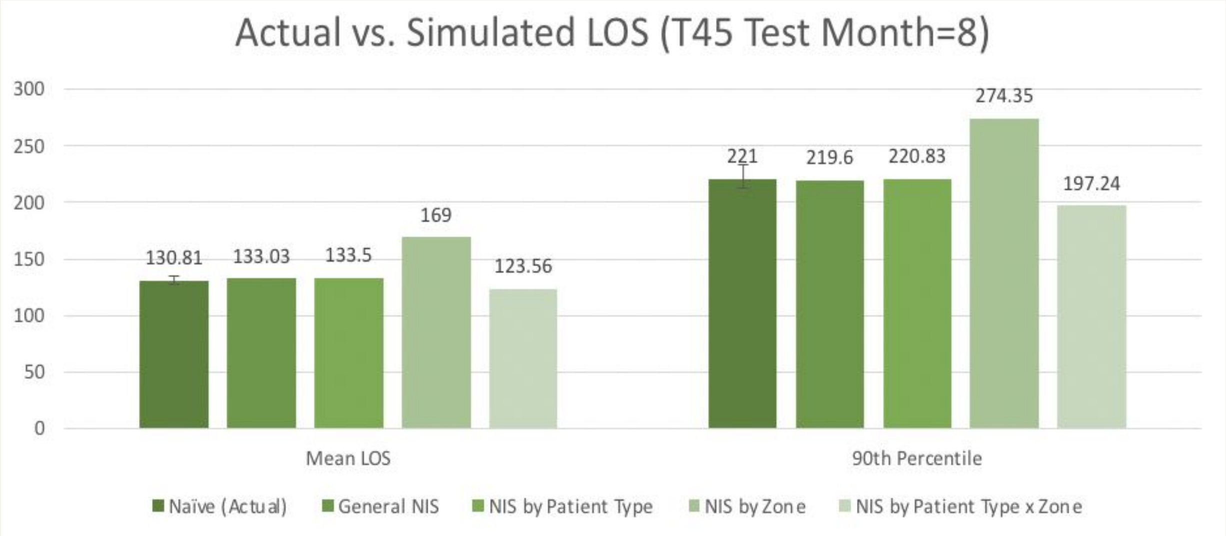


- General NIS and Patient-type NIS models estimate mean and 90p LOS fairly well
- More complex models (Zone NIS and Patient+Zone NIS) do not

Mean 95% CI: (223.81, 231.6)
90th Percentile 95% CI: (399, 416)

Actual vs. Simulated LOS, T45

Goodness of Fit: Mean & 90th Percentile Predictions (in Minutes)



- General NIS and Patient-type NIS models estimate mean and 90p LOS quite well
- More complex models (Zone NIS and Patient+Zone NIS) do not

Mean 95% CI: (127.11, 134.5)
90th Percentile 95% CI: (213, 234)

Model Diagnostics

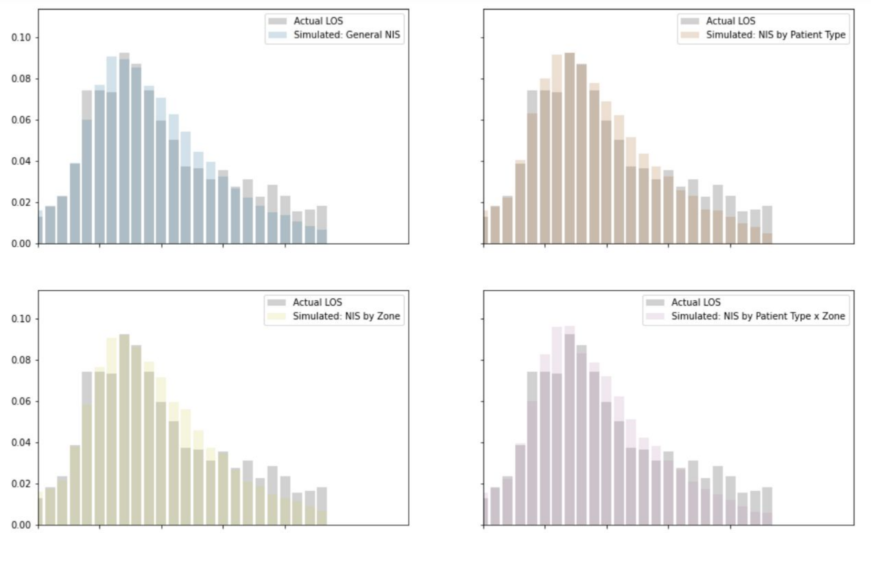
- More sophisticated analysis: examining histograms and Q-Q plots of LOS
- Using Kolmogorov-Smirnov statistic to analyze differences between simulated and observed LOS distributions

General NIS (State 0)	NIS by Patient Type (State 1
NIS by Zone (State 2)	NIS by Patient Type and Zone (State 3)

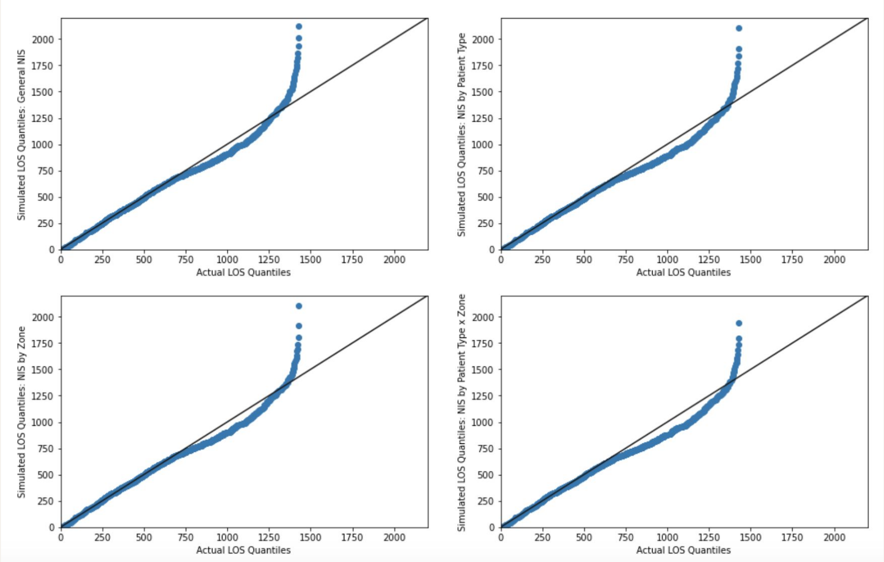
Patient Type: T123 Admitted

Goodness of Fit: LOS Distribution

Relative Frequency Histograms



Q-Q Plots



Patient Type: T123 Not Admitted

General NIS (State 0)

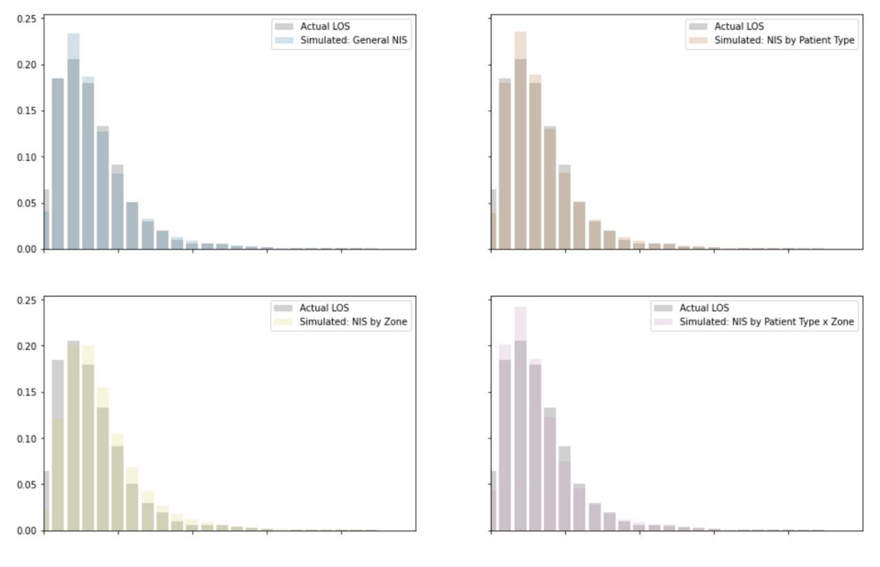
NIS by Patient Type (State 1

NIS by Zone (State 2)

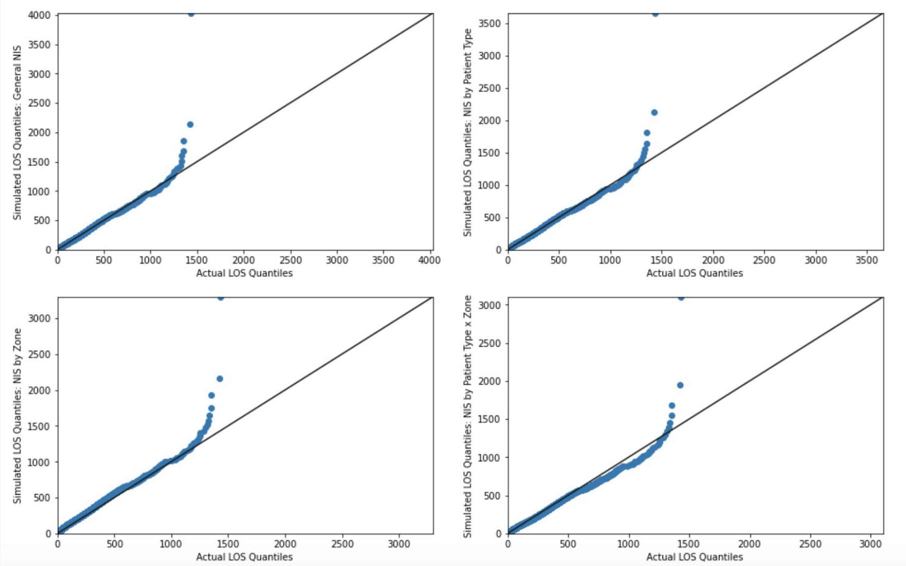
NIS by Patient Type and Zone (State 3)

Goodness of Fit: LOS Distribution

Relative Frequency Histograms



Q-Q Plots

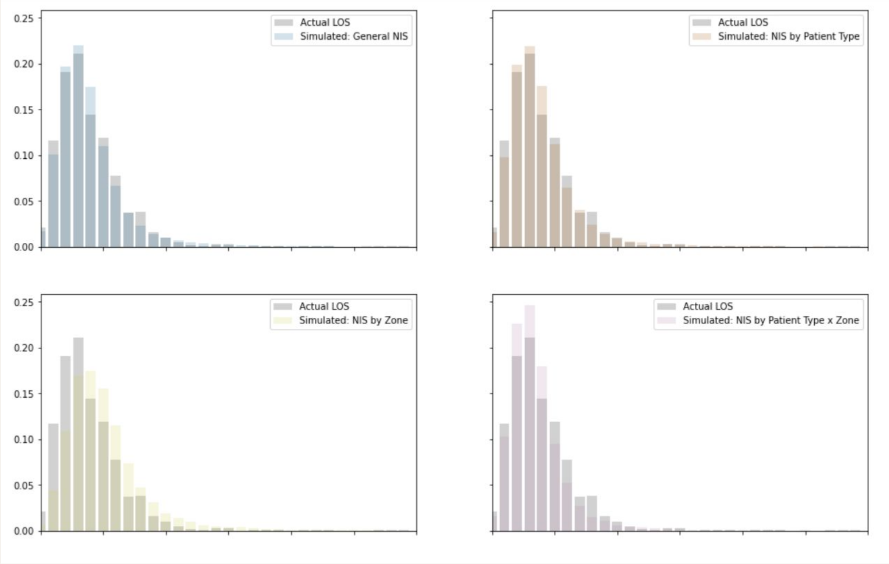


Patient Type: T45

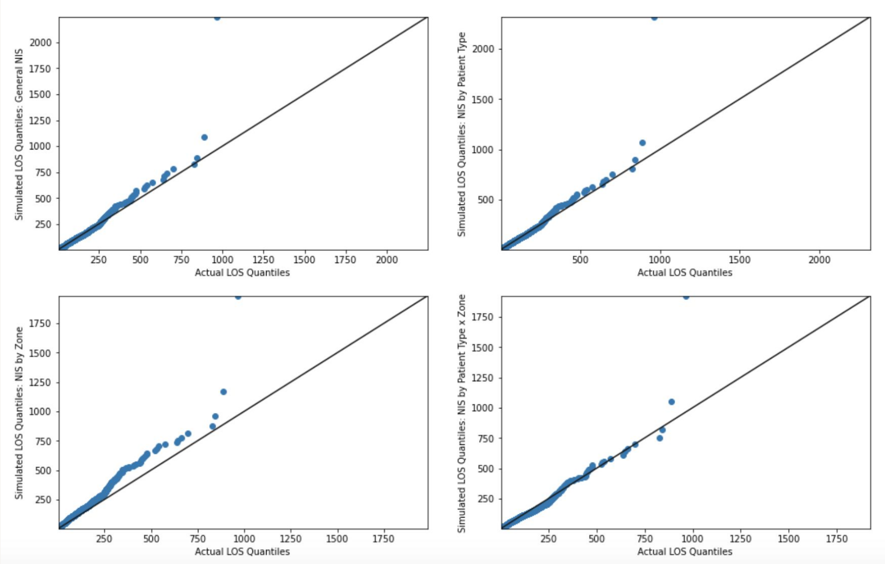
Goodness of Fit: LOS Distribution

General NIS (State 0)	NIS by Patient Type (State 1
NIS by Zone (State 2)	NIS by Patient Type and Zone (State 3)

Relative Frequency Histograms



Q-Q Plots



KS Test Statistics

Goodness of Fit: LOS Distribution (Smaller KS test statistic suggests better fit)

	System State 0	System State 1	System State 2	System State 3
T123A	**0.0447**	0.0545	0.0496	0.0641
T123NA	**0.0379**	0.0429	0.118	0.0441
T45	**0.0315**	0.0351	0.217	0.0884

Best Model: Model with System State 0 (General NIS)

	Histograms and Q-Q Plots	KS Test
System State of the “Best” Model(s)	Winner: General NIS Runner-up: Patient Type NIS	Winner: General NIS Runner-up: Patient Type NIS
“Best” in terms of	Deviation from the 45-degree line	KS test statistic

Intervention Analysis

Reducing LOS of consult patients by 10%, 20%, 30%, 40%, and 50%

August 2018

Used General NIS model to estimate Impact

Applying Intervention

Baseline

"**Naive**" (Obtained From Data), No Intervention
(For Validating Random Forest Models)

Patient Arrives

Sampled From Random Forest Models

System State 0 (General NIS)

Patient's Predicted LOS

Is this a **Consult** patient? If yes...

Apply Intervention*

E.g., If intervention is 10% cutdown:
LOS = LOS x 0.9

***Interventions**: 10%, 20%, 30%, 40%, 50% Reduction in Consult Patient's LOS

Mean & 90th Percentile LOS (No Intervention)

	Mean LOS			90th Percentile LOS		
	T123 Admitted	T123 Not Admitted	T45	T123 Admitted	T123 Not Admitted	T45
	Current Situation			Current Situation		
Baseline	10.28 hrs	3.79 hrs	2.18 hrs	19.04 hrs	6.77 hrs	3.68 hrs
General NIS Model	10.20 hrs	3.85 hrs	2.22 hrs	17.76 hrs	6.94 hrs	3.66 hrs

Note: all results shown are for General NIS model. Results for Patient-type NIS are quite similar.

Mean & 90th Percentile LOS (10% Reduction)

Mean LOS

	T123 Admitted	T123 Not Admitted	T45
	Current Situation		
Baseline	10.28 hrs	3.79 hrs	2.18 hrs
General NIS Model	10.20 hrs	3.85 hrs	2.22 hrs
	Reduce consult patients' LOS by 10%		
LOS Now	**9.20 hrs**	**3.76 hrs**	**2.15 hrs**
Total Time Reduced 1st and 2nd order	59.8 mins	5.2 mins	3.8 mins
Est. 1st Order Reduction	59.1 mins	1.7 mins	0.6 mins
Est. 2nd Order Reduction	0.7 mins	3.5 mins	3.2 mins

90th Percentile LOS

	T123 Admitted	T123 Not Admitted	T45
	Current Situation		
Baseline	19.04 hrs	6.77 hrs	3.68 hrs
General NIS Model	17.76 hrs	6.94 hrs	3.66 hrs
	Reduce consult patients' LOS by 10%		
LOS Now	**16.00 hrs**	**6.76 hrs**	**3.55 hrs**
Total Time Reduced 1st and 2nd order	105.8 mins	10.8 mins	6.5 mins
Est. 1st Order Reduction	105.3 mins	3.6 mins	0.4 mins
Est. 2nd Order Reduction	0.5 mins	7.2 mins	6.1 mins

Mean & 90th Percentile LOS (20% Reduction)

Mean LOS

	T123 Admitted	T123 Not Admitted	T45
	Current Situation		
Baseline	10.28 hrs	3.79 hrs	2.18 hrs
General NIS Model	10.20 hrs	3.85 hrs	2.22 hrs
	Cut down consult patients' LOS by 20%		
LOS Now	**8.21 hrs**	**3.68 hrs**	**2.10 hrs**
Total Time Reduced 1st and 2nd order	119.4 mins	10.2 mins	7.2 mins
Est. 1st Order Reduction	118.2 mins	3.4 mins	1.2 mins
Est. 2nd Order Reduction	1.2 mins	6.8 mins	6.0 mins

90th Percentile LOS

	T123 Admitted	T123 Not Admitted	T45
	Current Situation		
Baseline	19.04 hrs	6.77 hrs	3.68 hrs
General NIS Model	17.76 hrs	6.94 hrs	3.66 hrs
	Cut down consult patients' LOS by 20%		
LOS Now	**14.26 hrs**	**6.58 hrs**	**3.45 hrs**
Total Time Reduced 1st and 2nd order	210.1 mins	21.5 mins	12.4 mins
Est. 1st Order Reduction	208.8 mins	7.4 mins	0.8 mins
Est. 2nd Order Reduction	1.3 mins	14.1 mins	11.6 mins

Mean & 90th Percentile LOS (30% Cut Down)

	Mean LOS			90th Percentile LOS		
	T123 Admitted	T123 Not Admitted	T45	T123 Admitted	T123 Not Admitted	T45
	Current Situation			Current Situation		
Baseline	10.28 hrs	3.79 hrs	2.18 hrs	19.04 hrs	6.77 hrs	3.68 hrs
General NIS Model	10.20 hrs	3.85 hrs	2.22 hrs	17.76 hrs	6.94 hrs	3.66 hrs
	Cut down consult patients' LOS by 30%			Cut down consult patients' LOS by 30%		
LOS Now	**7.21 hrs**	**3.60 hrs**	**2.05 hrs**	**12.53 hrs**	**6.41 hrs**	**3.38 hrs**
Total Time Reduced 1st and 2nd order	178.8 mins	14.9 mins	10.3 mins	313.9 mins	31.5 mins	16.6 mins
Est. 1st Order Reduction	177.3 mins	5.1 mins	1.7 mins	311.2 mins	11.0 mins	1.4 mins
Est. 2nd Order Reduction	1.5 mins	9.8 mins	8.6 mins	2.7 mins	20.5 mins	15.2 mins

Mean & 90th Percentile LOS (40% Cut Down)

Mean LOS

	T123 Admitted	T123 Not Admitted	T45
	Current Situation		
Baseline	10.28 hrs	3.79 hrs	2.18 hrs
General NIS Model	10.20 hrs	3.85 hrs	2.22 hrs
	Cut down consult patients' LOS by 40%		
LOS Now	**6.22 hrs**	**3.53 hrs**	**2.00 hrs**
Total Time Reduced 1st and 2nd order	238.3 mins	19.1 mins	13.1 mins
Est. 1st Order Reduction	236.3 mins	6.8 mins	2.3 mins
Est. 2nd Order Reduction	2.0 mins	12.3 mins	10.8 mins

90th Percentile LOS

	T123 Admitted	T123 Not Admitted	T45
	Current Situation		
Baseline	19.04 hrs	6.77 hrs	3.68 hrs
General NIS Model	17.76 hrs	6.94 hrs	3.66 hrs
	Cut down consult patients' LOS by 40%		
LOS Now	**10.81 hrs**	**6.26 hrs**	**3.31 hrs**
Total Time Reduced 1st and 2nd order	417.1 mins	40.8 mins	21.1 mins
Est. 1st Order Reduction	414.0 mins	14.3 mins	2.5 mins
Est. 2nd Order Reduction	3.1 mins	26.5 mins	18.6 mins

Mean & 90th Percentile LOS (50% Cut Down)

Mean LOS

	T123 Admitted	T123 Not Admitted	T45
	Current Situation		
Baseline	10.28 hrs	3.79 hrs	2.18 hrs
General NIS Model	10.20 hrs	3.85 hrs	2.22 hrs
	Cut down consult patients' LOS by 50%		
LOS Now	**5.24 hrs**	**3.47 hrs**	**1.95 hrs**
Total Time Reduced 1st and 2nd order	297.4 mins	22.7 mins	15.8 mins
Est. 1st Order Reduction	295.4 mins	8.5 mins	2.9 mins
Est. 2nd Order Reduction	2.0 mins	14.2 mins	12.9 mins

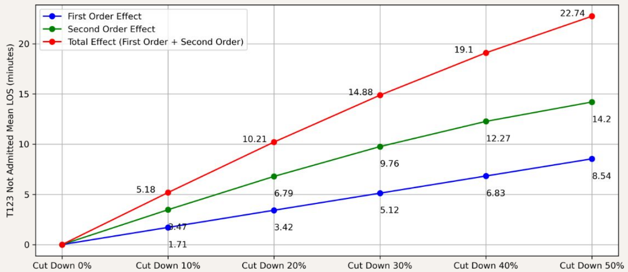
90th Percentile LOS

	T123 Admitted	T123 Not Admitted	T45
	Current Situation		
Baseline	19.04 hrs	6.77 hrs	3.68 hrs
General NIS Model	17.76 hrs	6.94 hrs	3.66 hrs
	Cut down consult patients' LOS by 50%		
LOS Now	**9.10 hrs**	**6.13 hrs**	**3.23 hrs**
Total Time Reduced 1st and 2nd order	519.5 mins	48.5 mins	26.1 mins
Est. 1st Order Reduction	514.7 mins	17.3 mins	3.8 mins
Est. 2nd Order Reduction	4.8 mins	31.2 mins	22.3 mins

Reduction on LOS with Interventions (in Minutes)

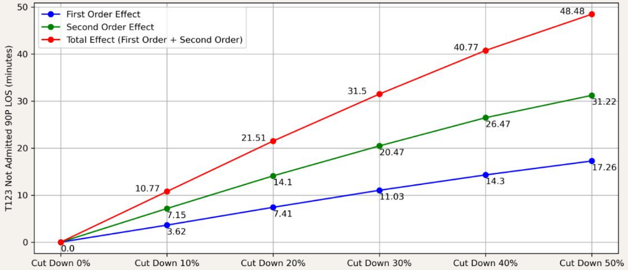
T123A

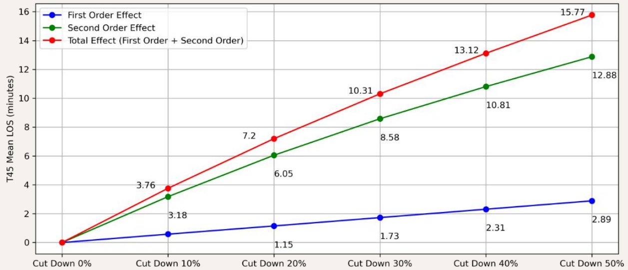
Mean LOS



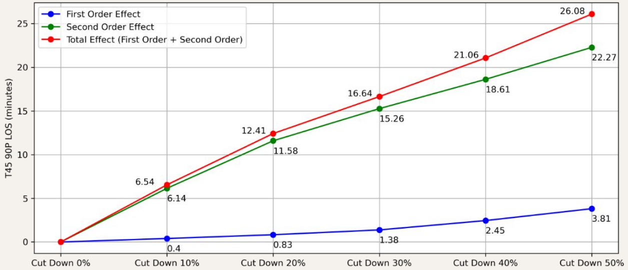
T123NA

90p LOS



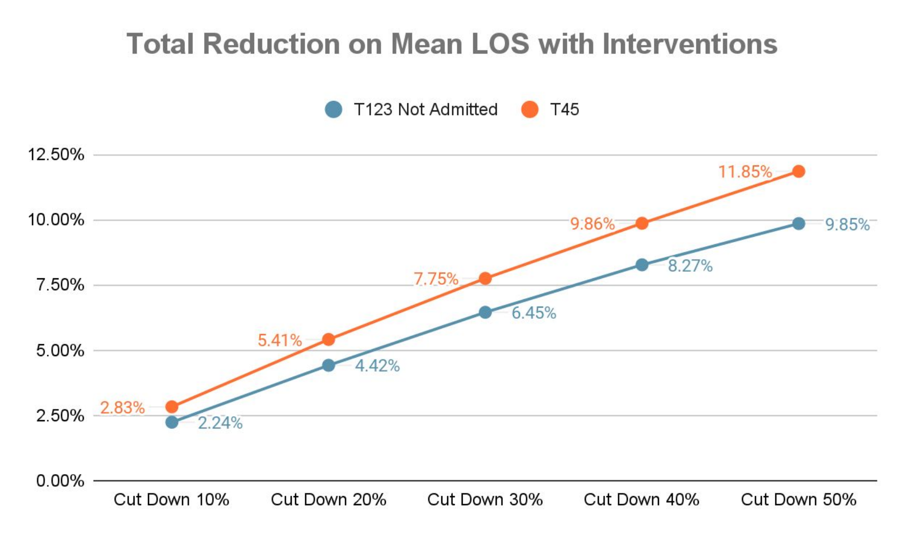


T45

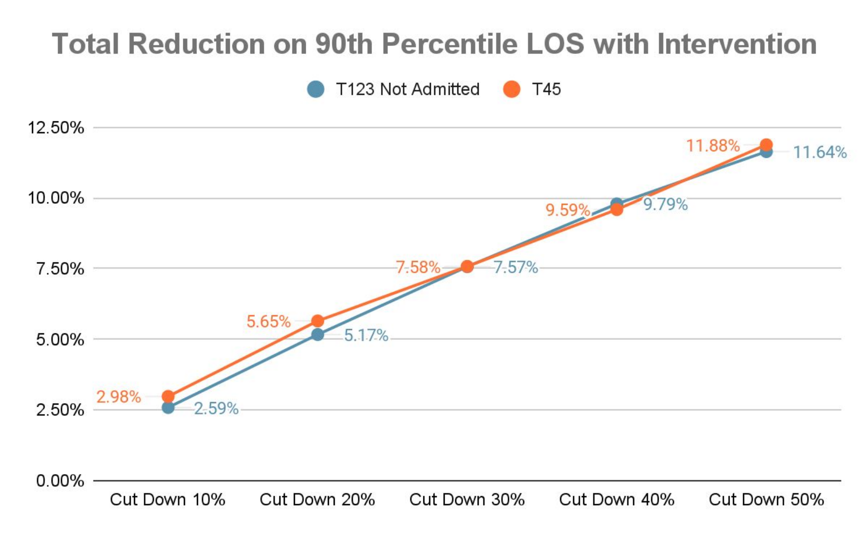


Reduction on LOS with Interventions (in Percentages)

Mean LOS



90th Percentile LOS



04

Conclusion

Limitations and Possible Future Direction

Main Conclusions

- Our simulation model is able to capture **Second Order Impacts**

- Second Order Impacts are observed in **T123 Not Admitted and T45 patients**
  - *These impacts are very substantial relative to the First Order Impacts*
    - *For T45 they dominate first-order impacts*
  - *However, since the First-Order Impacts are very small, the Second-Order Impacts are quite small as well in absolute values.*

- Reducing the LOS of consult patients **will reduce the LOS for all patients, but the reductions will not be very large in absolute terms**
  - *T123 Admitted patients: **insignificant second order effect***
  - *T123 Not Admitted & T45 patients: **50% consult patients LOS cut down** results in **~12% reduction** in 90th percentile length of stay (mainly due to second order effects)*

ServiceMiner

- This work is part of our larger initiative to construct ServiceMiner tool
  - An automated, data-driven simulation engine
- ServiceMiner combined Machine Learning, Queueing analysis, Simulation and Optimization Models
- Results can be used to analyze wide range of system interventions
- Main input: accurate event log data
- Our research team is looking forward to continued collaboration with NYGH

Key Limitations

- Models view the ED process as a “black box”
  - NIS is computed upon patient arrival to triage
  - For patients with large LOS, the NIS later in the process is likely much more relevant
- Ideally, would like to build separate models for various sus-stages of ED visit (triage, initial assessment, bloodwork, consult, etc.)
- For each stage, would use NIS in this stage and in the system overall
- However, need log times to execute (time of arrival to this stage, time of completion)
- Currently, only reliable time stamps are triage and “left ED”
- Better data may lead to better estimates of 2-nd order effects

Limitations & Future Directions

	Limitations	Future Directions
Data	• Data from **2018** (not very recent) • Training and testing data **limited** to a few months	• Consider trade-off between **recency vs. adequacy** of training and testing data
Arrival & Service Processes	• "**Black-box**" service process (lack of good log data for processes within the ED)	• Generate **synthetic arrivals** into the ED system • Infer **resource capacity** (n servers) in simulation • Model LOS on **individual station-level**
Process Abstraction	• Representation of congestion ("system state") is **highly simplified**, by counts of patients in the ED	• Discover **alternative ways** to improve system state representation

Thank You

Do you have any questions?