Adopting Advanced Analytics to Generate Health System Insights

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CDAO Canada Conference | Toronto | March 31, 2023







Our Organization

- **Digital and Analytics Strategy Division** supports policy development, program design, quality improvement, and accountability by transforming data into insights and insights into strategic guidance.
- Drives digital innovation and develops information strategies and policies to strengthen health system.

Five business branches focused on:

- Health data management
- Health analytics and insights
- Advanced analytics and data science
- Digital strategy
- Information management strategy and policy



Health Data Science Branch

Descriptive Diagnostic Predictive Prescriptive Cognitive analytics analytics analytics analytics analytics "What happened?" "Why did it "What may "What should be "What does it happen?" happen?" done?" mean?" Artificial intelligence **Business intelligence**

Analytics is made up of subspecialties that address specific questions:

Our diverse team includes methodologists, epidemiologists, and data scientists with expertise of advanced analytics methodologies and tools that provide support and solutions in diagnostic, predictive, prescriptive, and cognitive analytics.

Strategic Priorities



Build technical capacity and expertise



Develop products to support decision making

Modernize IT infrastructure



Design processes for scalable deployment





Data Holdings and Tools

Billings data at the invoice level (e.g., ADP, OHIP, ODB)

- Hospital, LTCH, and home care administrative data at the episode level (e.g, DAD, NACRS, CCRS, CPRO, HCD)
- Registry data at the individual level (e.g., RPDB, CPDB, CAPE)
- Population health data at the case level (e.g., CCM, COVAX)
- Daily hospital and LTCH census summary data (e.g., DBCS)
- Socio-economic status data at the DA level (e.g., Census, Environics)
- Web data (e.g., Twitter feeds, Indeed job postings)
- Image data (e.g., OHIP ultrasound image data)
- Population estimates and projections at the region, age, and sex level from the Ministry of Finance





ORACLE



Power BI



Growing Digital and Data Capacity in Ontario's Health System

Up to 2018 Building foundational digital and data infrastructure	•	 Clinical viewers and provincial data repositories: Digitized patient health records were made available to over 160,000 frontline clinicians through central repositories Frontline provider systems: Nearly every hospital and majority of community-based physicians (80%) use a hospital information system, electronic medical record, or other digital charting and communication tool

2018 to Curr	ent
Growth of digital tools a	nd
data insig	hts

- Virtual care is a mainstream component of OHIP and widely used
- Interoperability was made possible and beginning to advance
- Data, analytics, data science advanced the government's management and response to COVID-19

2022 and beyond Realizing the value of Ontario's digital and data assets

Health data and digital assets are governed as provincial significance:

- **Digital and data driven health system:** Support the health system priorities and transformation through digital, data, and analytic services and tools
- Collect once and use many times: Enable use of integrated data from across sources
- Integrated and real time data: Empower the ministry as a leader in health data analytics, data science, and insights to support evidence-informed policy, planning, and investments in high value services

Advanced Analytics in Action

Three recent examples of generating health system insights through advanced analytics:

Comparative Study of Machine Learning Techniques to Forecast Dementia ED Visits and Unplanned ED Visits

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COVID-19 Forecasting Using an Interactive Extended SEIR Forecasting Application

Developing a Risk-Adjusted Indicator for Thirty Day Mortality of Trauma Cases in Ontario



Comparative Study of Machine Learning Techniques to Forecast ED Visits for people living with Dementia

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Machine Learning Models



Project objective: To test performance of ML techniques on dementia data.

Implemented machine learning models to forecast ED visits for people living with dementia:

- Long short-term memory (LSTM)
- Bidirectional Long short-term memory (BiLSTM)
- S4
- DeepAR
- Transformer



Performance of Prediction Models for ED Visits by people living with dementia

• For each method, we applied two common measures to measure the relative quality of predictions, the root mean square error (RMSE) and mean absolute error (MAE) and also considered calculation time.

	Evaluator		
Model	RMSE	MAE	Computation time (s)
S4	16.0	11.3	2956
Bidirectional Long short-term memory (BiLSTM)	12.9	8.6	1218
DeepAR	15.9	10.1	10600
Long short-term memory (LSTM)	14.1	9.6	1274
Transformer	12.3	8.1	456



Prediction Result with Transformer for ED Visits by people living with dementia in Ontario

Year	Unplanned FD Visits	%
lea		Change
2015	125,860	
2016	131,072	4.1%
2017	138,820	5.9%
2018	141,403	1.9%
2019	143,327	1.4%
2020	145,327	1.4%
2021	149,429	2.8%
2022	151,514	1.4%
2023	156,035	3.0%
2024	155,108	-0.6%
2025	156,489	0.9%
2026	157,152	0.4%
2027	157,358	0.1%
2028	160,378	1.9%
2029	157,615	-1.7%
2030	157,674	0.0%
2031	157,581	-0.1%
2032	157,600	0.0%
2033	157,546	0.0%



Prediction Result with Transformer for ED Visits at Sub-Region Level





COVID-19 Forecasting Using an Interactive Extended SEIR Forecasting Application



Project Objectives

- Development of Extended-SEIR modeling tool, which can be customized to meet evolving needs and maintained internally
- Reduction of the time required to tune and adjust model parameters and produce new forecasting results
- Development of an interactive user interface to allow both internal team members and external client users to create forecasts without coding



Background – SEIR Model



- SEIR is a standard model that is widely used by epidemiologists to model disease outbreaks.
- Forecasts how a disease will evolve in a population by categorizing how people progress across four states – Susceptible, Exposed, Infectious, and Resolved





Model Features



- SEIR forecasting model that produces forecasts for the number of Infected, Hospitalized, Critical and Fatal
- Dynamic variables such as infection rate which can be defined based on either a user-defined series or a function
- Allowing users to model average, best- and worst-case scenarios
- The model can automatically load-in initial values and can use them to "prime" the model and start from real world conditions
- The model can take checkpoints as parameters which allows users to build detailed scenarios and assumption both in the future and retrospectively



Forecasting App Demo



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SEIR Model Calculator File Data View	Primary Scenario 🗢 General Age Groups Checkpoints
Loading	Rates
	Reproduction Rate
	2.3
	Population Susceptible
	% 40 ♦ 200 200 500 500 1000
	Initial Infected to Hospitalized Factor
	40
	0.0 20.0 40.0 60.0 80.0 100.0
	initial exposed to infected Factor
	1.0 20.0 40.0 60.0 80.0 100.0
	Initial Number Of Beds
	Con Enabled
	ICU
	▲ 0 0 2000 4000 5999 7999 9999
Health Data Science Branch	Hospital
	▲ 0 0 2000 4000 5999 7999 9999
	Temporal
	Real Date Range
	2022-01-01 2022-01-15
	Simulation Start
	Out of range
	Simulation Time
	iii 100
	7 7 100 150 222 293 365
	Hospitalization Stay Time
	1 8 19 37 54 72 90



Developing a Risk-Adjusted Indicator for Thirty Day Mortality of Trauma Cases in Ontario

Purpose of a Trauma Mortality Indicator





Objectives:

- To report trauma centre performance
- To facilitate high standard of care



Trauma Case Definition



CASES WERE EXTRACTED FROM THE ONTARIO TRAUMA REGISTRY, WHICH RECORDS INJURIES WITH A MINIMUM 'ABBREVIATED INJURY SCORE'.

CASES MEETING SIX DEFINING CRITERIA AGREED UPON BY A TRAUMA WORKING GROUP WERE USED FOR THE ANALYSIS.

Mortality definition: Death within thirty days of centre arrival

14327 cases

1639 deaths (11.4%)

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Trauma centres in Ontario



Map created by Health Analytics Branch, Health System Information Management Division (February 2017)

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Concerns with a crude thirty day mortality by centre

Patient population might be different across centres in terms of:

- Patient demographics
- Patient comorbid conditions
- Patient acuity
- Size of patient population

Measure of hospital performance should account for differences across centres that are outside of the hospital's control

Risk adjusted mortality

• Probability of mortality estimated for each patient using a logistic regression model that accounts for:





Model results: Risk adjusted vs crude mortanty rate, by centre (FY 2012 – FY 2015)

WHEN RISKS ARE FACTORED IN TO CALCULATIONS, THERE IS CONSIDERABLY LESS VARIATION IN MORTALITY RATES AMONG CENTRES.

To summarize

- Risk adjusted odds ratios shows that compared to overall average:
 - Two centres have lower likelihood of thirty day death
 - One centre has higher likelihood of thirty day death
- Risk adjustment moderates the crude mortality indicator across centres
- Risk adjusted centre performance fluctuates over time
- Better data capturing practices by centres to reduce missing values may improve accuracy of results

Methodological notes

- Risk adjusted mortality rate is used to report performance of trauma centres
- Hierarchical logistic model was used for risk adjustment
- Model performance was strong (c-statistic = 0.89)

THANK YOU!

QUESTIONS?