The Decision Uncertainty Toolkit

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Canadian Network for Modelling Infectious Diseases

Réseau canadien de modélisation des maladies infectieuses

Strengthening the community of people who are making and using infectious disease models to improve public health both inside and outside of Canada





Models were an important part of decision making during the COVID-19 response internationally



The NEW ENGLAND JOURNAL of MEDICINE

WRONG BUT USEFUL

Wrong but Useful — What Covid-19 Epidemiologic Models Can and Cannot Tell Us

Inga Holmdahl, S.M., and Caroline Buckee, D.Phil.



Successes and Challenges

- The explicit use models for decision making on such a large scale.
- Huge opportunity for evidence-informed decision making.
- Not all decision makers were prepared to interface with modellers, and vice-versa.
- When there are gaps in the communication of model assumptions and uncertainty, the results of models are difficult to interpret for decision makers.

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Why are we doing this? The Problem

- Decision makers are typically provided infectious diseaser epidemic control (ID) models in many forms, some with mean values only, mean values with some uncertainty bands, and/or scenarios.
- Means do not provide information about outcome uncertainty and therefore risk.
- Important for skewed distributions such as cases, hospitalizations, or deaths.

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ALBERTA CANADA

• Essentially, decision makers can be unaware of the risk associated with alternative policy options, and/or without tools to consider this risk.



https://www.canada.ca/en/public-health/services/publications/diseases-conditions/covid-19-using-data modelling-inform-public-health-action-april-28-2020.html

CANADA'S COVID-19 SCENARIOS

A look at the federal government's long range forecast for the COVID-19 epidemic if individuals increase, maintain or decrease their current rate of contacts:



https://www.cbc.ca/news/politics/phac-modelling-covid19-1.5874530

Some Types of Modeling Uncertainty

- <u>Structural assumptions</u> i.e., SIR or SEIR , how many vaccine compartments? model selection methods (Portet, 2020)
- <u>Parameter assumptions</u>: i.e., one-way sensitivity, probabilistic sensitivity analysis or PSA, partial rank correlation coefficient (PRCC) methods etc. of known, unknown, and/or estimated parameters

 <u>Decision uncertainty:</u> e.g., scenarios, what should we do? Risk tolerance i.e., <u>scenario A is under</u> a threshold, but 95% UCL is very high versus scenario B is over the threshold, but 95% UCL is not as high?



What are we doing? The Aim

- Adapt and build from health economics methods to characterize, visualize, and communicate decision risk, for infectious disease models.
- Develop the 'Decision Uncertainty Toolkit' in partnership with decision makers and ID modellers
 - Visualization tools
 - New measures of risk
 - R bookdown document with standard description text and codes (living repository)



The Decision Uncertainty Toolkit

Visualizations, Risk Measures, & Descriptions



Part 1: Visualizations I



Probabilistic one-way sensitivity



https://link.springer.com/article/10.1007/s40273-019-00869-3 https://www.originlab.com/www/products/GraphGallery.aspx?GID=599



Raincloud Plots

Part 1: Visualizations II





Part 2: Risk Measures I

- Work with decision makers to define policy thresholds that can be used to measure risk **across scenarios**
- Evaluate uncertainty in outcomes relative to these thresholds
 - Quantitative risk measures
 - Relative comparisons across scenario alternatives
 - Cumulative threshold (risk over time)



Part 2: Risk Measures II



Quantitative risk measure

Expected Risk =
$$\left[\sum_{n=1}^{N} (\max(D, O) - D)\right]/N$$

D = decision threshold, O = observed outcome, N= #simulations

- Interpretation of risk value is easier with a relative comparator (ex. what does a value of 370 mean?)
 - Define a 'baseline' comparator and calculate relative values
 - Ex. baseline risk is 500, scenario risk is 370
 - (370-500)/500 = -0.26, so risk is reduced by 26%
- What about over time? Bad outcomes can persist
 - Sum the risk measure over fixed time period
 - Dynamic threshold value or weights



Part 3: Descriptions

Descriptions of toolkit elements

 Standard descriptions and examples for each toolkit element

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 Aim is to use common or example language that has been supported by decision makers through engagement Descriptions of approaches to uncertainty

 ID modellers use methods to communicate uncertainty e.g. 95% CI bands.

 Aim is to describe different approaches to communicating uncertainty that is supported by modelers through engagement

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Example Decision Scenario



Example: Decision Scenario

Decision maker is selecting between multiple policies:

- A. Baseline do nothing
- B. Intervention 1 e.g., close schools
- C. Intervention 2 e.g., mandatory masking
- D. Intervention 3 e.g., close schools + mandatory masking

<u>Policy target</u>: keep hospitalizations under 700 (capacity maximum)

Note: All these graphs are synthetic simulations and used for illustration purposes only

















time

time

. 150









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Quantitative risk measure

Expected Risk =
$$\left[\sum_{n=1}^{N} (\max(D, O) - D)\right]/N$$
 Expected Risk_t = $\left[\sum_{t=t_{min}}^{t_{max}} \sum_{n=1}^{N} (\max(D_t, O_t) - D_t)\right]/N$

D = decision threshold, O = observed outcome, N= #simulations

- Expected risk considers the magnitude and density of curves from a decision threshold (D)
- These values are relative compared to a baseline scenario, but are better interpreted as a percentage change from baseline as a quantity of risk



Expected Risk_t =
$$\left[\sum_{t=t_{min}}^{t_{max}} \sum_{n=1}^{N} (\max(D_t, O_t) - D_t)\right]/N$$

	Baseline	Intervention 1	Intervention 2	Intervention 3
Expected risk	47,661	4,777	4,035	1,374
Policy risk impact	-	-90%	-92%	-97%

- Time range: 0 to 199 days
- Relative comparison to baseline model (no intervention)
- Interpretation of expected risk is relative to baseline
- e.g., for Intervention 1 (4777 47661)/47661 = -90%



	Baseline	Intervention 1	Intervention 2	Intervention 3
Risk	47,661	4,777	4,035	1,374
Policy risk impact	-	-90%	-92%	-97%







Next Steps

- Engagement with ID modelers:
 - Donation of scenario data samples to try with the decision uncertainty toolkit
 - Inputs on application to current modelling initiatives and descriptions/wording
 - Can provide a working version of decision uncertainty toolkit code for feedback. The results obtained could be helpful for us for discussions with decision makers ?
- Engagement with decision makers
 - Examine risk tolerance
 - Feedback on descriptions/wording and decision uncertainty risk measures and graphs i.e., what works, what could be better, what is needed?
- Dissemination
 - R bookdown to provide modelers the ability to read in simulated modelling runs for various scenarios and generate visuals and risk measures
 - Repository of descriptions, vignettes, and suggested communications for decision uncertainty
 - Manuscript



Interested in Workshops?

- Please contact Nicole Oak at <u>noak@ihe.ca</u> if you are interested to participate in workshops by January 5, 2024. In the email, if you can provide us:
 - Contact information
 - Role: ID modeler, decision maker, and/or other
 - General availability in January 2024
- We will send out a doodle for dates and times that will maximize participation for the workshops
- Your feedback, insights, and suggestions will help complete this work



Thank-you

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