# Interpretable Machine Learning

Application To Triage And Reassessment Guidelines For Ventilator Rationing

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## Scarce health resources during the pandemic

• The COVID-19 pandemic has highlighted the challenges of managing life-saving health resources



Figure 1: New York Times, 12/23/20

• Role of official triage guidelines: promote trust, transparency & consistency

#### Goals in this project

- Evaluate existing guidelines, in terms of numbers of lives saved
- Learn novel interpretable guidelines
- Incorporate ethics and fairness criteria
- $\bullet~\rightarrow$  For this we will use data & analytics

Collaboration with the Critical Care Team and clinical ethicists at Montefiore/Albert Einstein College of Medicine (NY)

# Ventilator allocation for COVID-19 patients

Key question: in case of shortages, who have the priority to ventilators?

- In the USA, 26 states have scarce resource allocation guidelines.
- Official NYS guidelines<sup>1</sup>, objective: number of lives saved.



Figure 2: Timing of the decisions in the NYS guidelines

 $<sup>^1 {\</sup>rm Zucker}$  et al. (2015). Ventilator Allocation Guidelines: New York State Task Force on Life and the Law

# Ventilator allocation for COVID-19 patients: triage

- Allocation decisions based on *SOFA*<sup>2</sup>: risk score in {0, ..., 18}. High SOFA indicates a severe health condition.
- Priority classes for intubation:
  - 1. blue/green = exclusion,
  - 2. yellow = intermediate priority,
  - 3. red = highest priority.

Triage Code on Initial Assessment	Criteria	Action or Priority for Vent, ECMO, HD, CVVH or critical care bed	
Blue	Exclusion criteria met Or SOFA > 11	<ul> <li>Manage medically without life-sustaining technology</li> <li>+/- palliative care</li> </ul>	
Red	SOFA* ≤ 7 or single organ failure	Highest priority for ventilator, life-sustaining technology or critical care bed	
Yellow	SOFA* > 8 and ≤ 11	Intermediate priority for ventilator, life-sustaining technology or critical care bed	
Green	No significant acute organ failure	Defer or discharge Reassess as needed	

Figure 3: NYS guidelines at triage

<sup>2</sup>Sepsis-related Organ Failure Assessment

# Ventilator allocation for COVID-19 patients: reassessment

- Allocation decisions based on SOFA: risk score in {0, ..., 18}.
   High SOFA indicates a severe health condition.
- Priority classes for intubation:
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Triage Code	Criteria at 48-hour Assessment	Criteria at 120-hour Assessment	Action or Priority for Vent, ECMO, CVVH, HD or critical care bed
Blue	Exclusion criteria met <u>OR</u> SOFA > 11 <u>OR</u> SOFA stable at 8-11 with no improvement from initial assessment	Exclusion criteria met OR SOFA > 11 OR SOFA stable at 8-11 with no improvement from second assessment	<ul> <li>Move to <u>extubation</u></li> <li>Manage medically after <u>extubation</u></li> <li>+/- paliative care</li> <li>Transfer to non-critical care bed</li> </ul>
Red	SOFA $\leq$ 11 and decreasing	SOFA < 11 and decreasing	Highest priority to continue with MV, ECMO, CVVH, HD or <u>or</u> critical care bed
Yellow	SOFA < 8 with no improvement from initial assessment	SOFA < 8 with < 3 points decrease in past 72 hours	Intermediate priority to continue with MV, ECMO, CVVH, HD or <u>or</u> critical care bed
Green	No longer on ventilator or passing weaning trials or life supporting tech	No longer on ventilator or passing weaning trials or life supporting tech	Extubate and reassess Transfer from critical care bed if not on ventilator

Figure 4: NYS guidelines at reassessment

#### Key questions in this presentation

- 1. Are NYS guidelines saving more lives than First-Come-First-Served?  $\rightarrow$  Should we revise guidelines?
- Can an interpretable policy save more lives than the NYS guidelines?
   → We use data and analytics to compute interpretable policies.
- 3. Should the triage decision also be based on demographics (age, BMI, etc.) and/or comorbidities (malignancy, diabetes, etc.)?

 $\rightarrow$  This may further disadvantage specific subpopulations who already face structural inequities.

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# Success of artificial intelligence in healthcare

Recent achievements<sup>3</sup>: IBM Watson, breast magnetic resonance imaging, operations scheduling, management of ICU beds and high-flow nasal cannula, etc.



Figure 5: Exponential growth of investment and data

 $<sup>^{3}</sup>$  Chan et al. (2012), Hwang and Bedrosian (2014), Bakker and Tsui (2017), Gershengorn et al. (2021), etc.

### Contrast: large body of literature vs. actual implementation

Most of AI methods **currently deployed** in the hospitals include automatized billing, fraud detection, nurses/operations scheduling ...

... but what about patients treatment?



Figure 6: (Projected) market shares by 2026 for AI in healthcare

# A key issue: interpretability

- Interpretability is crucial to operationalize guidelines.
- Most artificial intelligence methods are *black box* methods.



# A simple model of interpretability: decision tree

- Various notions of interpretability<sup>4</sup>: sparsity, linear models, index-based rules ...
- Here, we focus on decision tree.



(b) Representation as a decision tree

<sup>&</sup>lt;sup>4</sup>Bertsimas et al. (2020), Atar et al. (2010)

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### Sequential decisions in healthcare

- Decisions in healthcare: sequential in nature.
- We use *tree policies* for interpretable sequential decision<sup>6</sup>:



<sup>&</sup>lt;sup>6</sup>Related to Ciocan and Mišić (2019) on interpretable stopping time.

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# Our method for computing sequences of decision trees

- We develop an algorithm to optimize sequences of decision trees...
- ... using backward induction from the last tree to the first tree.



 $\rightarrow$  We use our model of sequences of decision trees to compute novel interpretable guidelines for ventilator allocations.

 $\rightarrow$  Decisions: intubate/extubate at 0h/48h/120h of intubation.

#### **Retrospective dataset**

- 807 COVID-19 patients
- Hospitalized at Montefiore (NYC) between March and June 2020
- Static information: demographics + comorbidities
- Sequential information: SOFA (risk score) updated every two hours
- Maximum number of ventilators used at the same time: 253.

### **Empirical setup**



Figure 9: Example of a patient trajectory in the hospital

#### Numerical experiments

- Simulation model to generate patients trajectories in the hospital
- Goal: how many lives saved by NYS vs. FCFS vs. Tree Policies?
- Input: number of ventilators available (for instance n = 200)
- Output: number of deaths if only *n* ventilators had been available

#### Insights from our simulations.

1. NYS guidelines save as many lives as First-Come-First-Served.

 $\rightarrow$  NYS guidelines have been designed in 2015, and are not adapted to the specifics of COVID-19.

2. Simple interpretable guidelines can diminish the number of additional deaths by 25 % compared to NYS/FCFS.

 $\rightarrow$  Crucial to use data to inform triage/reassessment decisions.

#### Insights from our simulations.

3. It may *not* be beneficial to include demographics/comorbidities in our decisions.

 $\rightarrow$  Simple decision rules based on SOFA are sufficient.

4. It is easier to identify patients who may not benefit from intubation, at reassessments (48h/120h of intubation) than at triage.

 $\rightarrow$  This suggests more proactive extubations rather than more triage decisions.

### **Conclusion and future directions**

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Tractable model for interpretable *sequential* decisions.

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Evaluation with different cohorts, changing the timing of reassessments (48h/120h of intubation), adaptive guidelines to incorporate ICU capacity...

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#### Thanks for your time!

Full paper under review, short paper accepted at *American Journal* of *Bioethics*.

Please feel free to reach out at grand-clement@hec.fr