# Summer Discussion MI2 August 26, 2021

Sickest-first policy & Predictive Models

for Liver Transplant Candidates in the US

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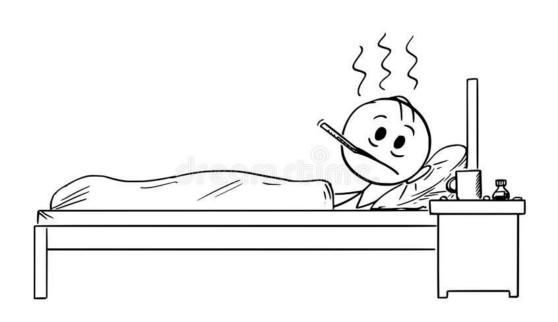
#### Outline

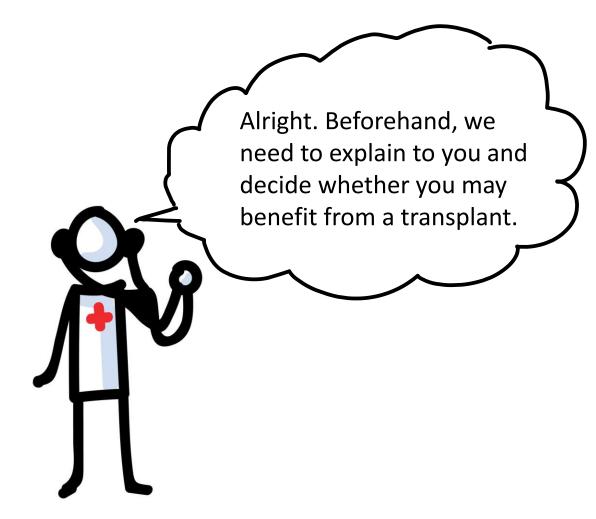
- 1/ Transplant problem and sickest-first policy
- 2/ MELD-Score and optimistic results
- 3/ Applying ML Techniques
  - Process of cleaning datasets
  - Models and obtained results from a paper
- 4/ Related works and Q&A section

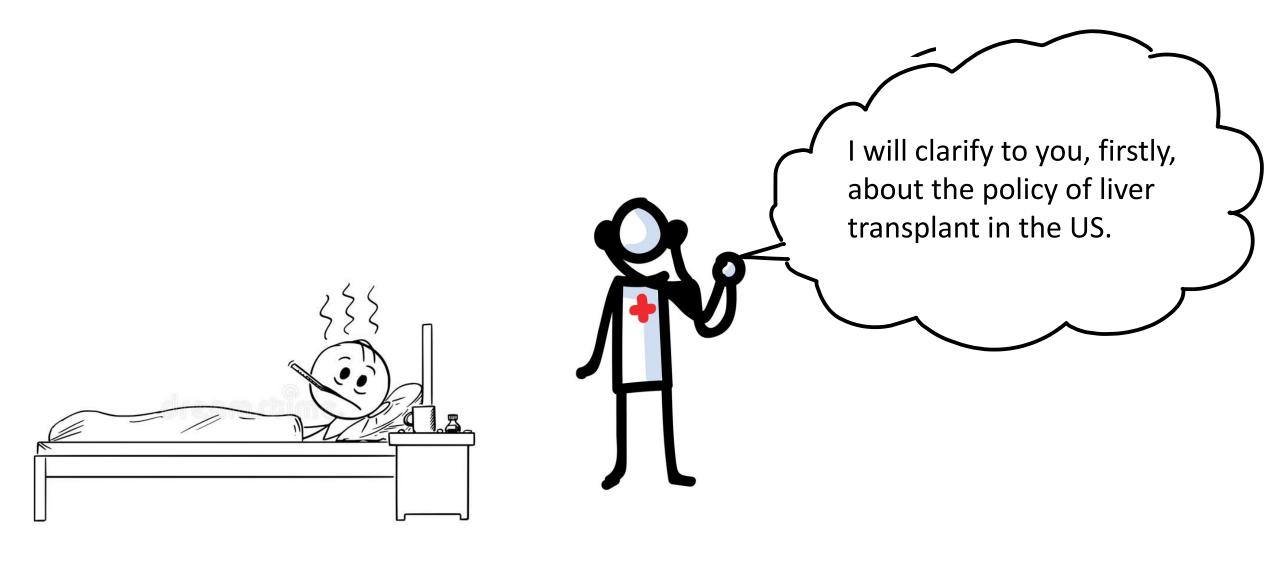
### Transplant problem & policy



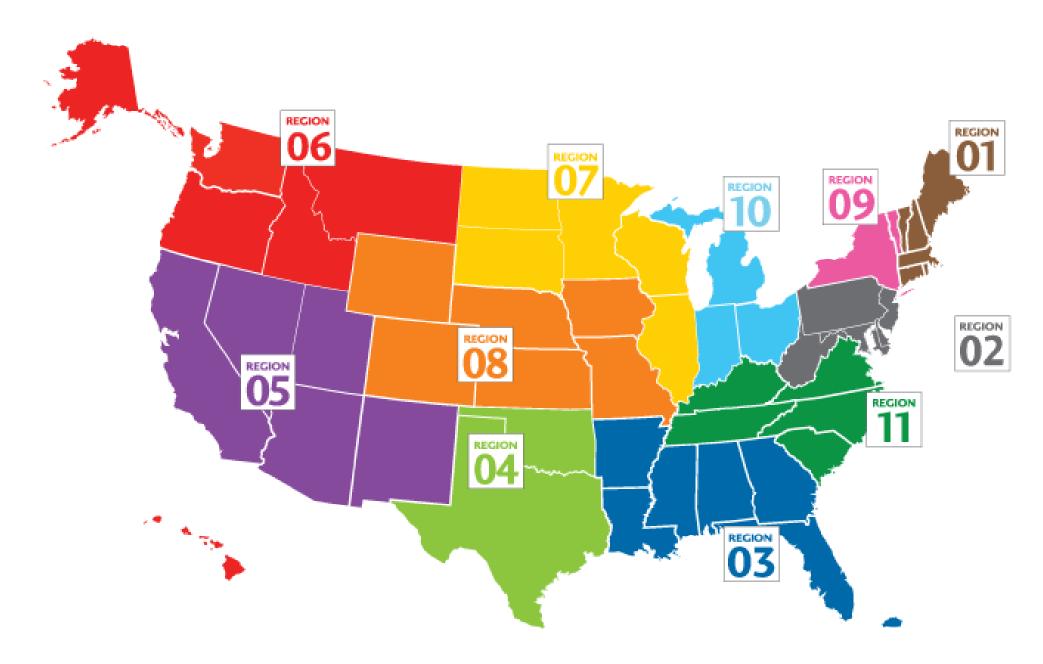
I am patient with end-stage liver disease. I need a livertransplantation.



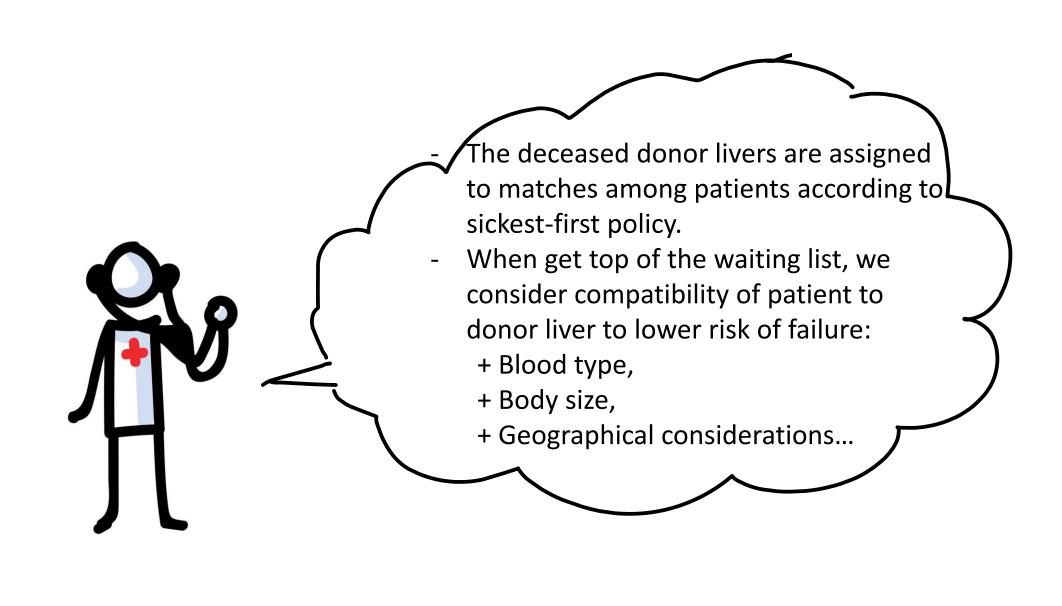


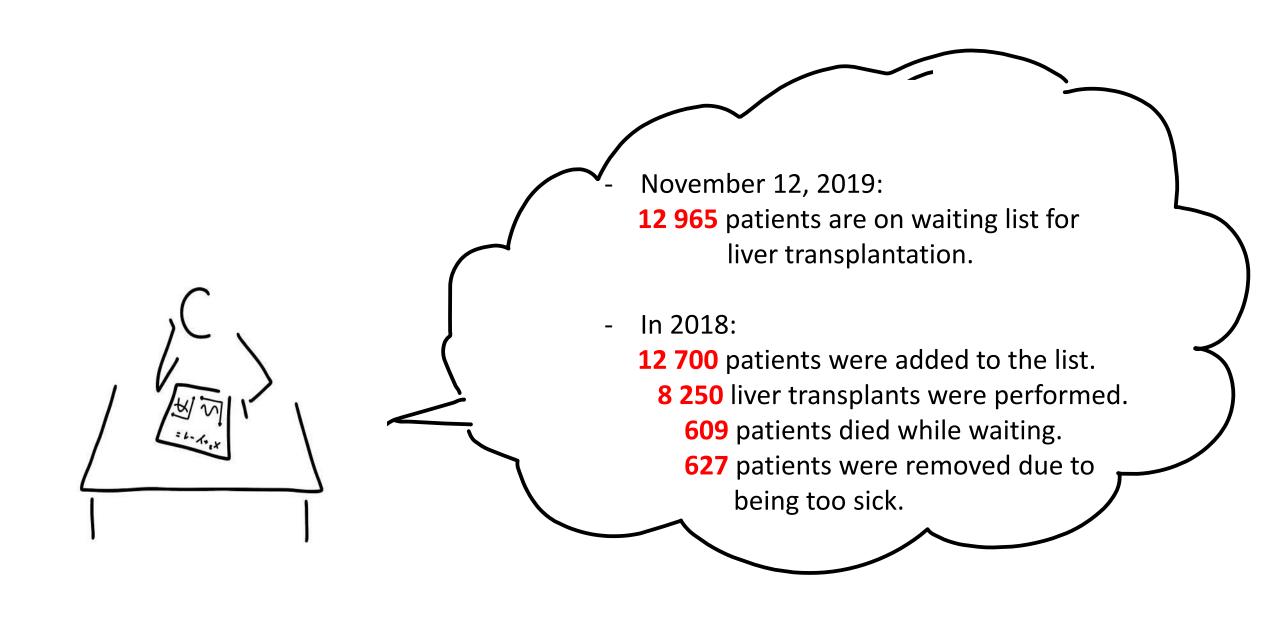






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# Problem of assessing disease severity of a patient

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- The Model for End-stage Liver Disease (MELD-score) estimates the chance of surviving during the next 3 months of patients with chronic liver disease.
- MELD-score is ranged from 6 to over 40
- The higher the score, the sicker the patient is, and the higher his/her position is in waiting list
- It has variants: MELD, MELD-Na, MELD-exception (for liver cancer, or hepatopulmonary syndrome,...) and PELD (for pediatric patients)

#### 3-Month Mortality Based on MELD Scores

MELD Score	<b>Mortality Probability</b>
40	71.3% mortality
30-39	52.6% mortality
20-29	19.6% mortality
10-19	6.0% mortality
9 or less	1.9% mortality

#### 1 Year Survival Rate Based on MELD Scores

MELD Score	Waiting list	Post Transplant
Score 10	90% survival	83% survival
Score 15	81% survival	80% survival
Score 20	63% survival	78% survival
Score 25	42% survival	74% survival
Score 30	21% survival	71% survival

As conditions change, MELD changes.

The table below shows how often MELD score gets updated.

MELD Score	Recalculation
25 or higher	Every week
19-24	Every 30 days
11-18	Every three months
10 or less	Once a year

### Formula of MELD-Score

MELD = 
$$3.78 \times \ln [Bili (mg/dL)] + 11.2 \times \ln [INR] + +9.57 \times \ln [Creati (mg/dL)] + 6.43$$

MELD-Na=MELD +  $1.32 \times (137 - Na) - [0.033 \times MELD*(137 - Na)]$ 

Bilirubin: how well liver clears substance "bile" (żółć) )

INR: how well liver makes proteins needed for blood to clot (krzepnięcie krwi)

Creatinine: how well kidneys work

Na: serum sodium, recently added, how well body regulates fluid balance.

Ranged from 125 to 137

### Formula of MELD-Score

MELD = 
$$3.78 \times \ln [Bili (mg/dL)] + 11.2 \times \ln [INR] + +9.57 \times \ln [Creati (mg/dL)] + 6.43$$

$$MELD-Na=MELD + 1.32 \times (137 - Na) - [0.033 \times MELD*(137 - Na)]$$

If Bili, INR, Creati < 1, use 1</li>

If Creati > 4, use 4

### Optimistic results from MELD-Score

The MELD-based allocation system was immediately successful, leading to the first ever reduction in the number of waiting list candidates and a 15% reduction in mortality among those on the waiting list.

Freeman, R., Wiesner, R., Edwards, E., Harper, A., Merion, R., Wolfe, R.: Results of the first year of the new liver allocation plan. Liver Transplant, **10**, 7-15 (**2004**)

### Drawbacks of MELD-Score based system

- The log-transformed values of Bili, INR, Creati at 1.0 can be problematic, as a large percentage waiting list candidates possess Creati levels below, and values below this threshold can reflect different levels of kidney function.

Sharma, P., Schaubel, D., Sima, C., Merion, R., Merion, R., Lok, A.: Re-weighting the model for end-stage liver disease score components.

Gastroenterology, **135**, 1574-1581 (**2008**)

- Correlation between MELD and outcome is not equally strong for all patients. For some patients, MELD may not accurately reflect the severity of their condition.

## It's high time for ML Models!!

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#### ML methods from a paper of 2021

## **Predicting Mortality in Liver Transplant Candidates**



Jonathon Byrd, Sivaraman Balakrishnan, Xiaoqian Jiang, and Zachary C. Lipton

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A. Shaban-Nejad et al. (eds.), *Explainable AI in Healthcare and Medicine*, Studies in Computational Intelligence 914, https://doi.org/10.1007/978-3-030-53352-6\_31

#### ML Pipeline

- Data: waiting list histories from June 30, 2004 to 2016
- Data division: 50-25-25% for train-val-test
- Out of sample test set.
- Metric: ROC AUC (concerning with giving livers to patients who most need them than accurately predicting mortality risk)
- Number of features: 50
  - 31 known at registration
  - o 19 updated over time

### Data preprocessing

- Cat features — dummy variables
- MELD & MELD-Na Score ← by formulae
- Missing values:
  - Numerical time-series features: forward-filled by last known value
  - o Other numerical missing values: by median from training set

After pre-processing, data has 241 columns

### Training model

Train models using four different feature sets:

o **First set:** all available features

o **Second set:** excludes demographic features: citizenship, education, gender,

ethnicity, blood type, income (age, height, and weight are kept)

Third set: excludes diagnosis, functional status,... (can be manipulated by doctors)

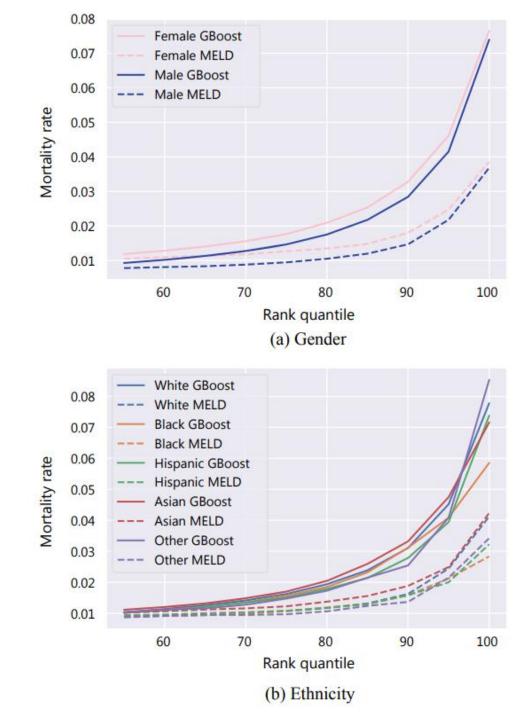
o **Fourth set:** only has: Bilirubin, INR, Creatinine, Na and dialysis twice in previous week

- Models: Logistic Regression and Gradient Boosting ensembles with decision trees
- Hyperparameters: detailed in the paper

### Obtained results

	All features	Non- demographic features	Selected features	MELD-Na features
Same-day mortali	ty			
MELD	N/A	N/A	N/A	0.825, 0.791
MELD-Na	N/A	N/A	N/A	0.831, 0.793
Match MELD	N/A	N/A	N/A	0.750, 0.729
Logistic Regression (same-day)	0.888, 0.867	0.886, 0.864	0.876, 0.855	0.817, 0.782
Gradient Boosting (same-day)	0.935, 0.920	0.931, 0.918	0.873, 0.857	0.793, 0.735
Logistic Regression (3-month)	0.881, 0.851	0.880, 0.849	0.872, 0.839	0.820, 0.774
Gradient Boosting (3-month)	0.902, 0.873	0.901, 0.873	0.894, 0.864	0.832, 0.796
3-month mortality	,			
MELD	N/A	N/A	N/A	0.715, 0.674
MELD-Na	N/A	N/A	N/A	0.730, 0.686
Match MELD	N/A	N/A	N/A	0.685, 0.651
Logistic Regression (same-day)	0.786, 0.756	0.786, 0.752	0.778, 0.745	0.700, 0.662
Gradient Boosting (same-day)	0.783, 0.767	0.781, 0.765	0.808, 0.781	0.731, 0.690
Logistic Regression (3-month)	0.820, 0.772	0.818, 0.770	0.809, 0.759	0.734, 0.687
Gradient Boosting (3-month)	0.834, 0.800	0.832, 0.798	0.827, 0.789	0.734, 0.696

### Obtained results



### Conclusions

- Gradient boosting ensembles outperform MELD and MELD-Na for AUC ROC
  - o 0.935 (grad-boost) vs 0.831 (MELD-Na) for same-day prediction
  - o 0.834 (grad-boost) vs 0.730 (MELD-Na) for 3-months prediction
- Removing demographic features (race, education, gender,...) and subjective features does not have a large effect on model performance
- Both model and MELD-Na slightly underestimate mortality in female patients, but no similar trends when comparing across ethnicities

### References

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- https://www.organdonor.gov/learn/organ-donation-statistics
- UNOS.org

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### Discussion Time