# Interpretable Machine Learning for Time Series Data in an ICU Setting

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# **KEY QUESTION**

Can we predict death with time series ICU data in an interpretable way?

#### **MOTIVATION**

- Interpretable ML could help doctors find important relationships
- Ample publicly available ICU data to perform machine learning on
- Many of open problems, especially in interpretability

## DATA

#### **Nature of ICU Data**

3D data (sequence, days, features)

Patient ID	Day since admission	Feature 1	Feature 
0	0	20	
	1	30	
1	0	25	

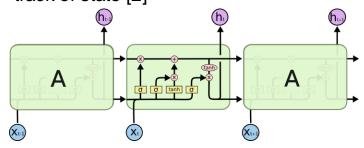
# MIMIC-III[1]

- Publicly available dataset with 57,272 unique hospital admissions
- Due to the large amount of data, only use patients with complete records (I.e. no imputation)
- Final features: 3 demographics, 9 biomarkers, 4 comorbidities
- 2870 patient admissions, 15097 days of complete data, 31% deaths

## **MODELS**

#### **LSTM**

Handles time series data by repeated application of a neural network, keeps track of state [2]



As well as LSTMs, want to use another model for a benchmark comparison

#### **Random Forests**

State of the art architecture [3], but can only handle 2D input

Suppress longitudinal input to predict:

- Death using first N days of data
- Death using last N days of data

## ML RESULTS

Baseline: 69% for guessing discharge RF using admission: 78% accuracy, f1 scores 0.64 for death.

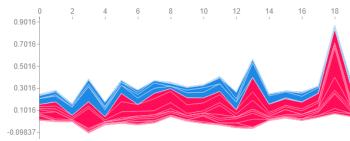
RF using final day: 84% accuracy, f1 scores 0.74 for death.

LSTM: 87% accuracy, f1 scores 0.75 for death, 0.91 for discharge.

LSTM accuracy is only 83% when using final day data, 86% for last 5 days

#### SHAP

- Model agnostic, local interpretability method [4]
- Uses 2D data. Well suited for RFs
- Remove sequence dimension to run LSTM in SHAP. Can plot these separate days together, see below



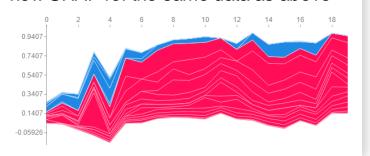
## **NEW SHAP**

- Time series explanations for SHAP don't match the model's output!
- SHAP is good for explaining features, but what about explaining a patient's entire ICU stay?

Proposed a modified version of SHAP.

- Exploit the nature of LSTMs and their internal state
- Need to modify ML model to take and return internal state

The below shows the output from the new SHAP for the same data as above

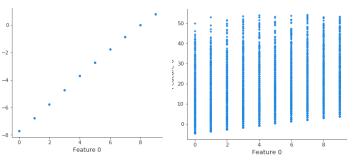


## **NEW SHAP RESULTS**

# **Sanity Checks**

#### Addition LSTM:

- Adds all numbers in a sequence
- What should the SHAP values be?



# Counting LSTM:

- Counts the length of a sequence
- Do any features contribute?

Can extract 'hidden state' contribution using the SHAP scores from the previous element in the sequence.

#### Limitations

How does the previous state affect features in the current time step?

# CONCLUSIONS

- 1. Modified SHAP seems promising for local explanations. Not a silver bullet
- 2. Lots more work in this space in the future

[2] C. Olah. (2015, Aug) Understanding Istm networks. [Online]. Available: https://col.ah.gith.ub.io/posts/2015-08-Understanding-LSTMs/ [3] S. M. Lundberg, et al., "Explainable AI for trees:From local explanations to globalunderstanding," CoRR, vol. abs/1905.04610, 2019

4] S. M. Lundberg and S.-I. Lee, "A unified approach to interpreting model predictions,"



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