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TEL-AVIV SOURASKY MEDICAL CENTER ICHILOV

Treatment Prediction in the ICU Setting using a Partitioned, Sequential Deep Time Series Analysis

Michael Shapiro[1,2], Yuval Shahar[2]

[1] Tel Aviv Sourasky Medical Center, Tel Aviv

[2] Department of Software and Information Systems Engineering (SISE), Ben-Gurion University

The challenge

- Physicians deal with complex medical situations and are required to make fast treatment decisions with significant repercussions.
- The current solution is to provide the clinician with a set of rigid and simple evidence-based rules, called *clinical guidelines.*
- It assumes the physician has made the **right diagnosis**, does not always specify the **correct dose**, and is considering each condition only at a certain moment in time, **ignoring the disease progression pattern** or the patients' **response to the initial treatment**.
- Such solutions ignore the context and might create an unnecessary variance in care among different care providers managing similar situations, or even within the care of the same provider (AKA "**Noise**" [Kahneman, Sibony, and Sunstein, 2021]).

The ideal solution

- A computational solution in the form of a **complete**, **context-sensitive**, **time-oriented and explainable** decision support system that can deal with complex real-life situations and provide guidance, error detection and education to the young physician.
- **Complete** = deals with a general case, including complex situations that may originate from several causes
- **Context sensitive** = The decision takes into account the patient's characteristics
- **Time-oriented** = Takes into account the change in the patient's state, its progression over time, and the patient's response to treatment
- **Explainable** = The proposed decision can be explained using accepted medical logic

Data and Objectives

General Setting:

- **Database:** MIMIC IV, containing 53,500 unique patients who stayed in Beth Israel Medial Center's ICU
- **Objectives**: Manage three common medical scenarios for which several causes and temporal trajectories might be possible, potentially modifying the course of therapy:
  - **Hypokalemia** – low blood potassium - 19,724 distinct clinical events
  - **Hypoglycemia** – low blood sugar – 6,313 events
  - **Hypotension** - low blood pressure (< 90/60 mm Hg) – 356,745 events

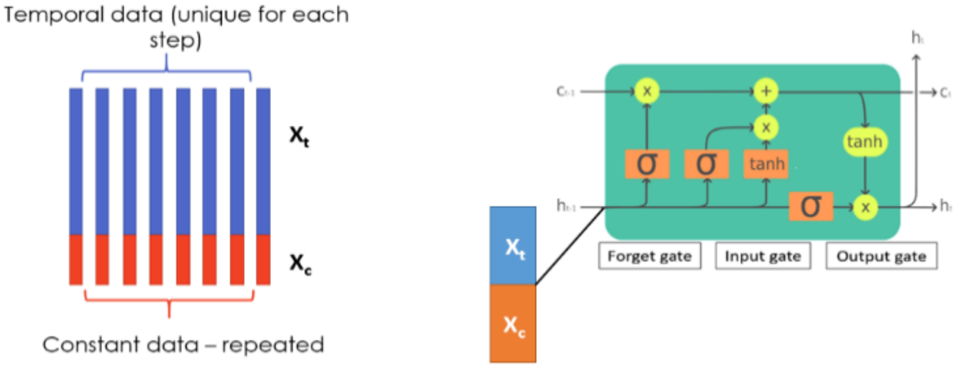
Computational Methods

- **Architecture:** An LSTM based neural network architecture:
    - Input containing data from the previous 24 hours prior to each decision
    - A multi-label binary and continuous dose prediction
    - Examination of several options for handling constant features
    - Partitioning the 12 hours time period, for which actions are predicted, into three four-hour windows

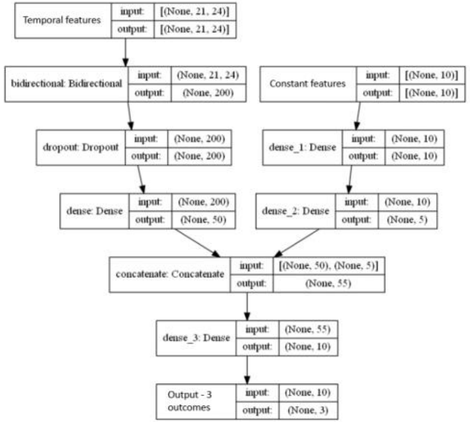
- **Goal: To mimic the actions of ICU clinicians at a top medical center in the USA**

Context-sensitive Predictions

Exploring the Optimal Use of Constant Features (e.g., demographics) via two options:



Internal inclusion of constant data in each datum



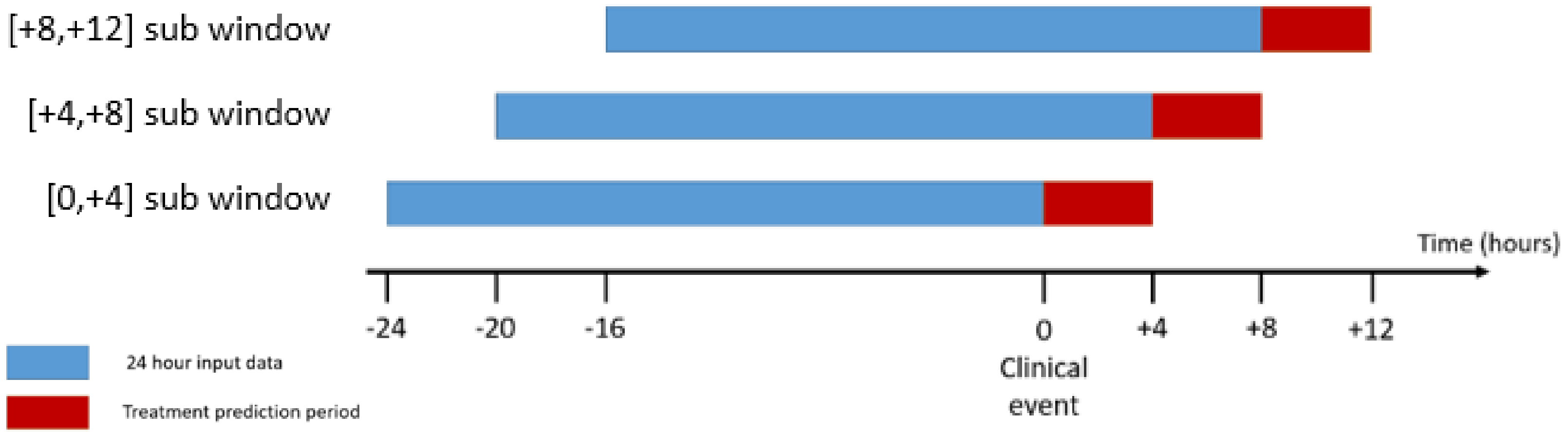
External inclusion of constant data by using a split network

Constant features : “Internal” vs “External”

	No constants	“External” model	“Internal” model
Hypokalemia	0.728	0.738	0.747
Hypoglycemia	0.711	0.738	0.739
Hypotension (fluids)	0.821	0.821	0.827
Hypotension (Dopamine)	0.944	0.945	0.953

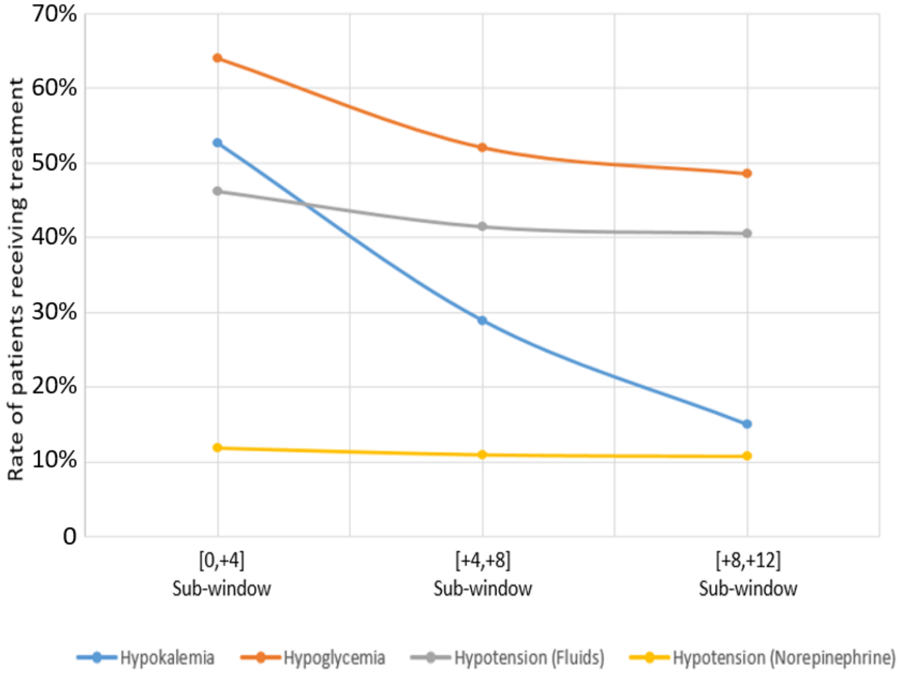
Since the “internal” model was slightly preferable and simpler, we stayed with it throughout the rest of the work.

The Partitioned Prediction Horizon



Each subsequent sub-window contains an input that begins four hours later and extends 4 hours to the future.

Change Across the Treatment-Prediction Time Window



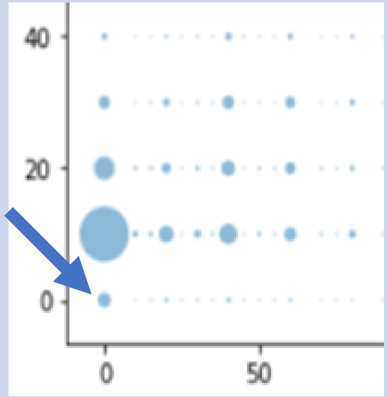
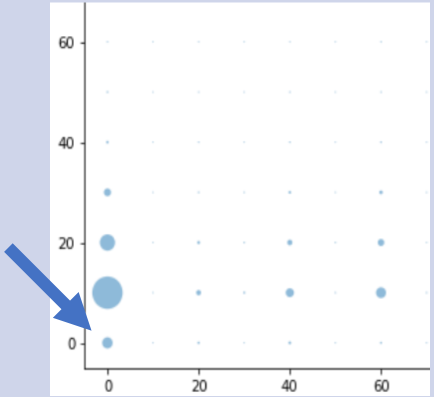
Utilizing Previous Sub-Window Data

- If the treatment process in the previous sub-window exhibits similarity, its data can be leveraged as additional training data to enhance the performance of the model. This is particularly beneficial when the number of available samples is limited.

	Base model	Using previous period data
Accuracy	0.660	0.681
AUC	0.727	0.746
MAE	11.739	10.726
MSE	21.584	17.226

Predicting No-Treatment Decision

- The dose prediction model struggles to predict “zero” treatment level for any kind of therapy decision

IV treatment	PO treatment
	

Predicted dose (mEq)

Actual dose (mEq)

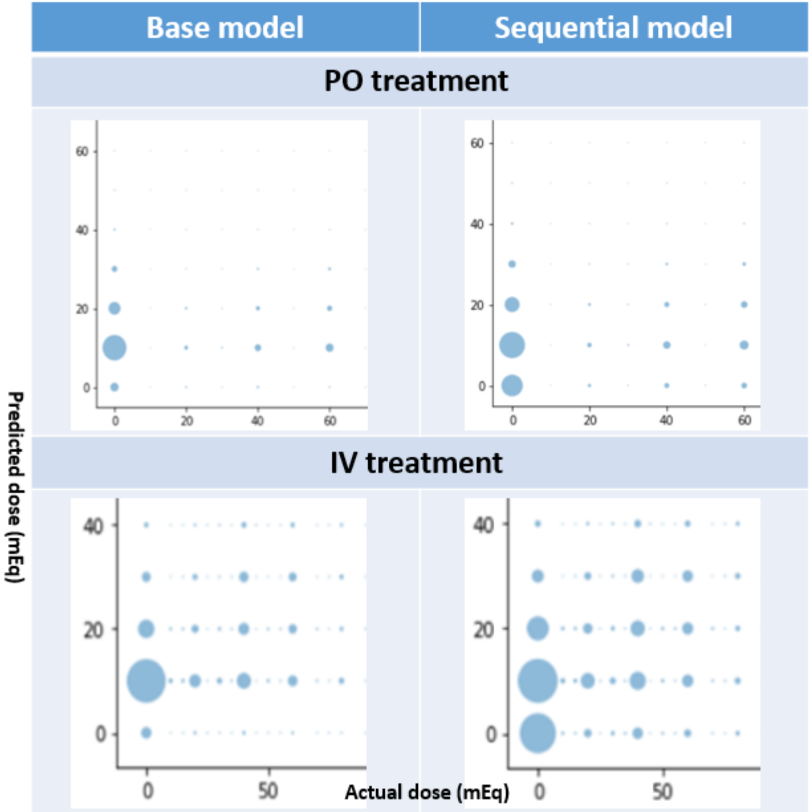
A Sequential-Prediction Model

We use in sequence two models:

- [1] **Binary classification** of <u>whether to treat</u>

When appropriate, followed by:

- [2] **Quantitative prediction** regarding the <u>magnitude of therapy</u>
- Both models were trained (in parallel) on all the data.
- **Note**: Predicting a "zero therapy" decision assists a less-experienced clinician in avoiding unnecessary therapy



Sensitivity to “No treatment” Decisions

	Base model	Sequential model
Hypokalemia - PO treatment	8.2%	32.6%
Hypokalemia - IV treatment	5.3%	36.8%
Hypoglycemia	1.3%	37.5%
Fluids	19.3%	75.1%
Dopamine	96.9%	99.8%
Norepinephrine	31.1%	95.3%

The base model even has a very low sensitivity to “no treatment” decision. The Sequential Model is essential to overcome this problem and help young physicians avoid unnecessary treatment.

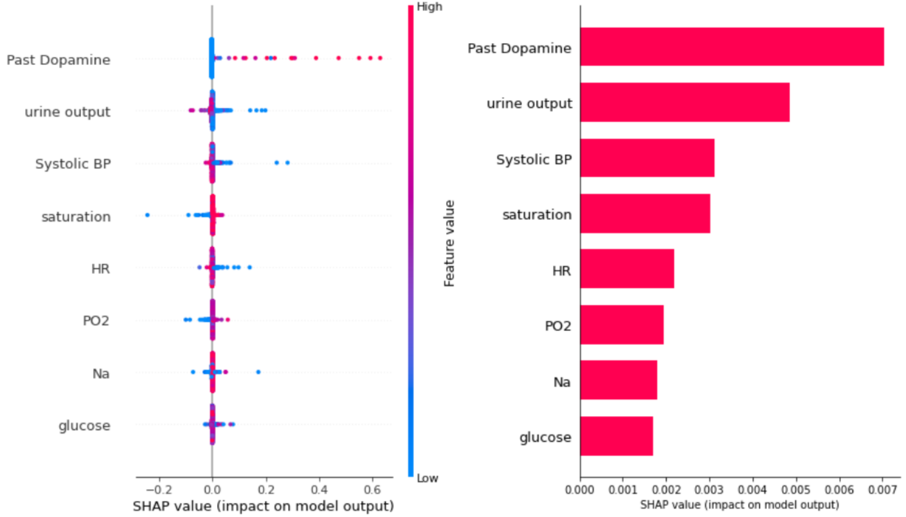
Improving Dose Prediction using Sequential Models

		Base model	Sequential model
Hypoglycemia	MAE MSE	13.996 23.340	12.936 22.896
Fluids (ml)	MAE MSE	149.7 334.05	130.1 338.0
Norepinephrine (mg)	MAE MSE	0.173 0.618	0.128 0.621
Dopamine (mg)	MAE MSE	0.628 6.363	0.356 6.418

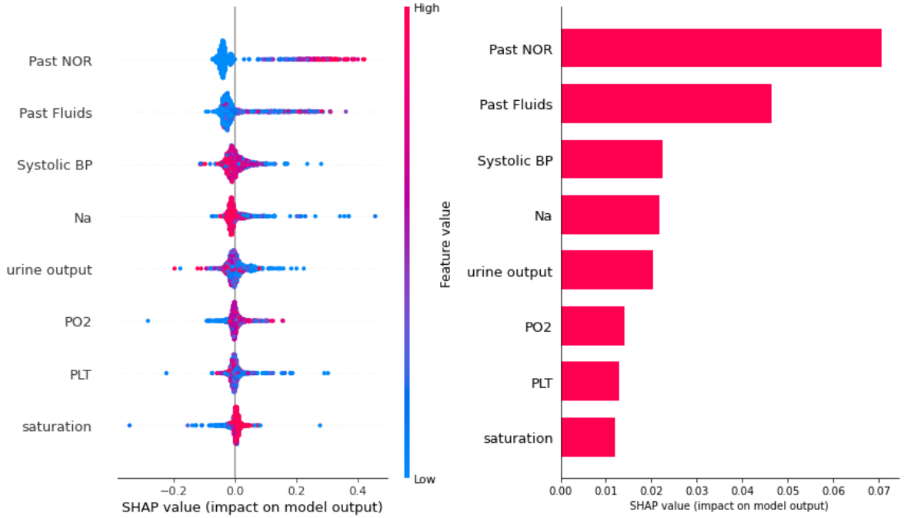
Providing Explanations

Explaining treatment options for hypotension (binary decision) reveals the different indications of the two vasoactive medication examined and hints that previously used practices that are now discouraged still "lurk" in the data – an important issue to address when designing a system to mimic physicians, since the training data implicitly includes older guidelines

Dopamine



Norepinephrine



Thank you!