MS1 - Blood Pressure Forecasting

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Abstract. In phase 1 of this project, we develop a sequence-to-sequence (seq2seq) neural network for predicting hemodynamics. The outcome of our model is Arterial Blood Pressure (ABP), and the features are time series for electrocardiogram (ECG), photoplethysmography (PLETH), carbon dioxide levels (CO_2), and historic ABP. We utilize data from VitalDB, which contains time-series health measures for 6,388 perioperative patients at 0.01-second time intervals. We build on prior research by solving an optimal control problem, where the control is the dosage rate of vasopressors and the outcome is stable, healthy ABP. The model utilizes an encoder-decoder architecture with an additional control mechanism as a feature. We predict two branches of outcomes, one with optimal control and one without. Solving an optimal control problem is pertinent because in settings such as remote care, recovery, urgent care, or understaffed hospitals, our optimal control system can be an important stopgap to prevent patient harm.

Key words. Prediction, Treatment Effect, Dynamical Systems, Optimal Control

1. Background and Motivation.

One of the main challenges in modern medicine is that patients respond very differently to the same treatment. According to the National Institutes of Health (NIH), approximately 40–60% of prescribed drugs fail to achieve the intended clinical outcome [3]. Beyond inefficacy, treatment misalignment often leads to adverse drug reactions (ADRs), which cause over 100,000 deaths annually in the U.S. and add more than $30 billion in avoidable hospital costs [4]. These statistics highlight a pressing need for systems that can predict, at the level of the individual patient, whether a given therapy will be effective and safe.

The broader vision of this project is to develop a personalized AI treatment efficacy predictor that leverages multi-modal clinical data to recommend interventions most likely to succeed for each patient. This problem is compelling because it sits at the intersection of machine learning, medicine, and patient safety, where improvements directly translate into saved lives and reduced healthcare costs. Since the semester is short, we will focus on drugs that modulate blood pressure, and if time allows, expand the scope to cancer drugs.

As an MVP and proof-of-concept, we focus on the intraoperative setting. Using the VitalDB dataset, which contains high-resolution physiological signals from over 6,000 surgical patients [7], we will model the relationship between patient signals (ECG, PLETH, CO_2, historic ABP) and vasopressor response. This domain is particularly interesting because peri-operative vasopressor dosing reflects the broader challenge of treatment efficacy: patient responses vary widely, the effects of incorrect dosing are immediate, and more accurate prediction could help reduce harm in both well-resourced hospitals and understaffed care settings.

A brief comment about terminology, when we mention optimal control, we are referring to optimal control theory and not control as used in causal inference. For the remainder of

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this project, please interpret the term control with respect to control theory and not causal inference unless explicitly stated.

2. Problem Statement. This project aims to determine whether sequence-to-sequence neural networks can accurately predict arterial blood pressure (ABP) trajectories and to find the optimal control function for vasopressor dosage rate, using peri-operative time-series data. Specifically, we seek to build a proof-of-concept model that demonstrates the feasibility of personalized, data-driven dosing prediction as a first step toward AI-enabled treatment efficacy prediction more broadly.

3. Data Sources. We use VitalDB as our primary data source [7]. The observation count is 6,388 surgical patients. The database contains three tables: clinical information, lab results, and hemodynamic health measures. The former two are cross-sectional, while the latter is longitudinal. The clinical information table contains data on patient demographics, type of surgery, and preoperative health measures, such as glucose levels and current prescriptions. A quick analysis shows that most surgeries are cancer-related. The lab results table contains data on a patient's pre-op labs, such as Prothrombin time (INR) and Hemoglobin. Lastly, the hemodynamic table is a time series of health measures along with aesthetics and other drug dosages. The length of a patient's time series is the length of the surgery. There is no shortage of data since the data is high-frequency, and surgeries tend to last over an hour. At a minimum, we observe that most patients have at least 3600 data points (using the largest time interval of 1 second). Data points can be increased by decreasing the time interval to 0.01 seconds.

The database is available via web API or a Python package vitaldb, which is a wrapper for the API. A table of summary statistics for patient demographics is shown in Appendix Table 1. With an API, we are able to integrate the data more easily into our app. The API is open-source with no limits, making the project tractable. If we find the data to be too messy, we can use another database called PulseDB, which is a distilled, cleaner version of VitalDB [5].

If time allows, we may use cancer data from Synapse. Synapse provides patient-level data and cancer regimen data. Both are cross-sectional, with any time series compressed to an interval. This would be a separate model, which takes in a drug regimen and outputs a binary variable for death.

4. Scope and Objectives.

4.1. Scope.

The scope of the project will be a working web app that takes in patient data, outputs ABP predictions along with a policy for blood pressure control. The app is meant to be used by doctors or nurses in a recovery or remote setting. It can also be used when a medical facility is over capacity. If the app predicts abnormal blood pressure levels, it will first notify the medical staff multiple times. If no one is available, then the system will utilize the optimal policy to administer drugs.

For our model, we will predict a sequence of ABP with a horizon of 10 minutes. We will present a function u_t that represents the optimal control (e.g., optimal dosage of vasopressors) over the time horizon. The optimal control portion takes inspiration from a paper on remote patient monitoring, which provides a strong use case for automating care in certain situations

[2]. We will train the model on VitalDB. For our demo, we will generate synthetic patient data to show how the app would work for patients in a real-world setting.

4.2. Objectives.

1. Collect and preprocess data in VitalDb
2. Develop a seq2seq model to generate predictions and derive an optimal control function.
3. Implement a scalable backend to handle multiple patients.
4. Design an intuitive and user-friendly frontend.

4.3. Learning Emphasis. The project emphasizes sequential neural networks for time series analysis and mathematical modeling via optimal control theory. The project also utilizes cloud computing architecture such as microservices, API endpoints, and a data pipeline.

4.4. Application Mock Design. Figure 1 provides a high-level overview of our seq2seq model. It takes in 5 time series and generates a hidden state vector. The hidden state vector will be used as input into the decoder and outputs ABP predictions, one with and one without a control mechanism, in order to compare. The encoder and decoder will both have convolution layers.

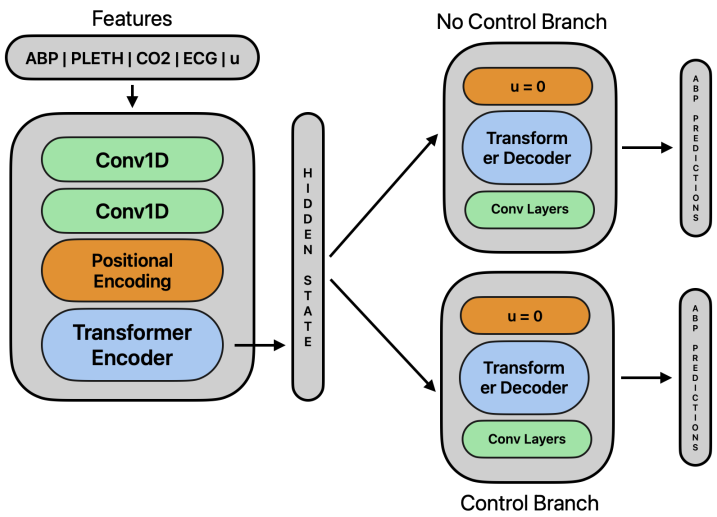

Figure 1. *Design of Model Prototype*

4.5. Research and Development. We conducted a literature review to understand how deep learning is applied in medicine, how VitalDB is used, and the gaps in the research. One paper used a transformer-based model with a binary output for hypotension [9]. Another used a U-Net architecture with a continuous outcome, cardiac output [8]. Similar to these papers, in many cases, the output was binary or scalar. There were no models that had a vector-valued output, which is the gap in research that we aim to fill with our seq2seq model.

4.6. Fun Factor. We build on existing research and attempt to build a novel model. The implications of the project are also large, given that rural hospitals in the U.S. suffer from

a shortage of doctors [**?**]. Providing a tool to ease the medical staff burden is much less expensive than hiring staff or providing incentives for doctors to move to areas that tend to have lower pay [1].

4.7. Limitations and Risks. There are a few limitations and risks to address. The first is that there is a possibility that we don't observe any relationship between the control variable and the outcome variable. In other words, the effect of the change in drug dosage isn't observed in the data. Another risk is the chance that the model is unable to capture the complex cyclical patterns. This is less likely because our model is a continuation of a model that was published in a paper. A more serious risk is the inherent bias in the data. The training data is composed of older, sicker individuals. This may compromise the external validity of our model. Finally, the cancer portion of our project may be intractable because most papers measure their drug response via tests on cell lines. Observational data may not be enough to train a model to predict the outcome of a cancer drug on a patient. Furthermore, cancer is a difficult illness to model because it affects nearly all of the human body; in contrast, blood pressure is mostly cardiovascular.

5. Milestones.

1. Familiarize with VitalDB, download the data, and preprocess the data.
2. Build a sequence-to-sequence model for ABP using the four features mentioned (ABP, PLETH, CO2, ECG)
3. Augment the model with a control u_t, which changes the dosage of vasopressors. The candidate vasopressors are norepinephrine, phenylephrine, vasopressin, and epinephrine.
4. If time allows, expand the model to cancer-based drugs using data from Synapse [6].

Appendix A. Tables.

	General surgery (n = 4,930)	Thoracic surgery (n = 1,111)	Gynecology (n = 230)	Urology (n = 117)	Total (n = 6,388)
Demographic					
Sex (male)	2,524 (51.2%)	618 (55.6%)	0 (0%)	101 (86.3%)	3,243 (50.8%)
Age (years)	59 (48-68)	61 (52-70)	45 (35-55)	64 (58-72)	59 (48-68)
Height (cm)	162 (156-169)	163 (156-169)	159 (155-163)	168 (161-173)	162 (156-169)
Weight (kg)	60 (53-69)	61 (54-69)	59 (53-66)	69 (62-77)	61 (53-69)

Figure 2. *VitalDB Demographic Summary Statistics*

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