1 Introduction

This memo is meant to be an initial document for the first week of the National Science Foundation's Mathematical Sciences Graduate Internsip Program (NSF MSGI). I am working under Dr. Gabriel Perdue of the Quantum Science Program at the Fermi National Accelerator Laboratory (FNAL). In this document I hope to outline the goals of the summer and the potential projects.

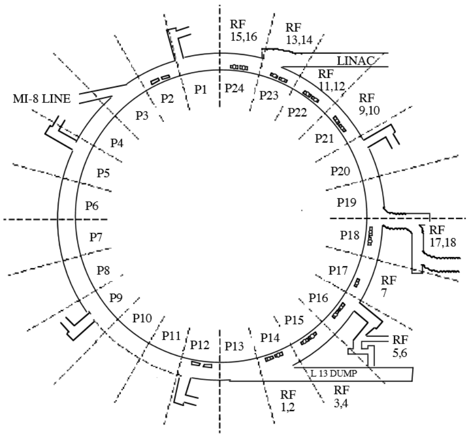

Figure 1: Booster Sketch, Source: [1]

2 Problem Introduction

A particle booster has some loss in particle beam. As of now, humans adjust certain parameters based on the reported losses. A sequence of operators (events) then play out over some (periodic) time horizon λ and the loss in beam is again reported. It is the goal of this project to construct an AI that is capable of making these adjustments. We hope to do so using reinforcement learning (RL). RL is appropriate for this poblem as it is a machine learning technique that leans a sequence of operators to minimize total loss over a possibly infinite time period.

3 Beginning Notes

The Fermilab (FNAL) Booster accelerator is a 74.47−radius, proton synchrotron, with an injection energy of 400 MeV and an extraction energy of 8 GeV, cycling at 15 Hz. It consists of 96 total magents over 24 periods, where periods are rays across the circumference swept out by $\frac{\pi}{6}$−radian slices of the circle (see Figure 1. A sinusoidal current is the driver of the magnets [1]. Power for these booster magents comes from the Gradient Magnet Power Supply (GMPS). Signals from the GMPS trigger a sequence of events over a time horizon (a supercycle) Λ. We are concerned with a sequence of events that occur over the horizon. These events are prescribed by a Time Line Generator (TLG) between the Booster and the Linear Accelerator (LINAC).

Over the horizon, a sequence of events, each selected from a set of admissible operators (events) $\mathcal{A}$, is prescribed. The operators are selected only at 15 Hz over the horizon, so that we have a total of 900 possible times to select operators. There are 256 possible events in $\mathcal{A}$, so that $|\mathcal{A}| = 256$. Any of the operators may be chosen at each time step. Therefore, over a horizon, we have a total of 230,400 possible choices. At any time, we may choose any of the 256 operators. so we have $900 \times 2^{256} \approx$ 1e+80 possible configurations. We are not seeking an optimal sequence of events.

3.1 B_VIMIN, B:VIMIN, B:IMINER

The primary variable we seek to influence is known as B:VIMIN, where B stands for "Booster," VI is the current, and MIN is minimum. Errors between a set current minimum, B_VIMIN, and the observed values B:VIMIN are reported as B:IMINER. This error is a function of some recorded input (unknown), where it takes the input (known to the machine) and divides by 3200. From basic analysis of the data,

$$\text{B:IMINER} = \gamma\ (\text{B\_VIMIN - B:VIMIN}),$$

where we found $\gamma \approx 0.055$.

4 Mathematical Formulation

4.1 Introduction

The ACNET console has a possible N variables, of which we sample 50 for the purposes of our problem. Let $\mathcal{V}$ be the set of all variables on the ACNET console, indexed by set $\mathcal{I}_{\mathcal{V}}$, and $\mathcal{U} \subset \mathcal{V}$ be the chosen sampling set. $\mathcal{V}$ (and hence $\mathcal{U}$) may be decomposed into two subsets: the set of dependent variables $\mathcal{O}$ which are observed output, and the set of independent variables $\mathcal{Q}$ which are tunable parameters.

The TLG dictates a set of 256 actions at 15 Hz over the horizon Λ. We let $\vec{E}_t \in \{0,1\}^{256}$ be a binary vector with coordinates indicating whether an event $\mathcal{E}_i, i \in \{0, 1, \ldots, 255\}$ is scheduled for time t. Data is drawn from 15Hz samplings of the beam. The events are signals to devices, and devices are set at the specified values held by the ACNET console. In particular, the events are signals turning on or off parameters in $\mathcal{Q}$.

4.2 Problem Statement

Given a vector of parameter values $\vec{p}_t \in \mathbb{R}^m$ and events encoded in $\vec{E}_t$, predict $\widehat{\Delta V}_t$ so that we update

$$p_1^t = \tilde{V} + \widehat{\Delta V}_t.$$

4.3 Verbose

Let $0 < n < N$ be the number of variables sampled (currently, $n = 50$). Further, let $\vec{p}_t \in \mathbb{R}^n$ be the values of the variables sampled at the index t, where the index is associated with a 15 Hz sampling over the time range of $\Lambda = (0, \lambda]$ seconds. We reserve p_1 to be the variable that we are able to modify. Furthermore, we let $\vec{q}_t$ be the values of the variables in the set $\mathcal{V} \setminus \mathcal{U}$.

As it is, we currently reactive system; it is reactive in the sense that it sets parameter p_0 according to a measured error ΔV from the previous time step. i.e. Given $\vec{p}_t, \Delta V_{t-1}$,

$$p_1^t = \tilde{V} + \Delta V_{t-1}.$$

The desired system will be proactive in the sense that we hope to predict ΔV, let it be $\widehat{\Delta V}$ for the time step that p_1 is set. i.e. Given $\vec{p}_t, \vec{E}_t$, predict $\widehat{\Delta V}_t$ so that we update

$$p_1^t = \tilde{V} + \widehat{\Delta V}_t.$$

5 Questions, Discussion, Future Steps

Data is saved by a console for 10-day time periods. We have begun to collect data over 1-day time periods for a sample of operators, parameters, and observations from the Booster.

5.1 Problem Analysis

- Data on the parameters $\vec{p}_t$ at time steps are available. The events $\vec{E}_t$ are not yet available.
- The problem at hand seems to be a supervised learning problem in the sense that we are not learning an optimal sequence of events but rather a function $\tilde{f} : \mathbb{R}^{|U|+|\mathcal{E}|} \to \mathbb{R}$, where again $\mathcal{U} \subset \mathcal{V}$ is the set of variables included in the study and $\mathcal{E}$ is the set of events. If $\vec{p} \in \mathbb{R}^{|\mathcal{U}|}$ and $\vec{E} \in \{0, 1\}^{|\mathcal{E}|}$, then

$$\widehat{\Delta V} = \tilde{f}(\vec{p}, \vec{E}),$$

  where $\widehat{\Delta V}$ is the predicted value for the offset ΔV.
- If it is an SL problem, what do we identify as "labels"?
- If it is an SL problem, then would Recurrent Neural Networks be a way or the best way to solve the problem?
- Can we pose this problem as a generative problem and use Generative Adverserial Networks to predict $\widehat{\Delta V}$ over the horizon $(T, T + \lambda]$ and subsequently "recommend" a tuning $p_1^t,\ t \in (T, T + \lambda]$, where T is some time stamp and λ is the horizon (the period of the TLG)?

5.2 Physics/Data Qs

- What are the losses logged? Can we obtain them?
- The horizon may be discretized– while time $t \in \lambda$, operators may only be selected at 15 Hz.
- Which operators in the admissible set $\mathcal{A}$ directly influence the parameter of consideration B:VIMIN? This is a question to be learned.

5.3 RL Qs

- Can we expand the prediction problem to a game where the AI learns the offset?
- Can we learn which events $\mathcal{E} \in \mathcal{A}$ correspond to changes in parameter observations (encoded as some coordinate $p_j \in \vec{p},\ j \in \mathcal{I}_{\mathcal{V}}$?
- Deep Q Learning is a dynamic programming problem of RL that uses a neural network to approximate the Q-function, an equivalent form of the sum over losses or rewards. We do not know the function generating the loss in the particle beam; we only have samples of the loss. Can we use a q-network to derive an approximate function to the loss?

References

[1] Crawford, John; Pellico, Bill; Morgan, Jim; Gattuso, Cons; Reyna, Juan; Drendel, Brian; Sullivan, Todd; Broy, Chuck; Meyhoefer, Aria; Chaurize, Salah; Newhat, Duane; Worthel, Bruce. *Booster Rookie Book* V 4.1. Fermi National Accelerator Laboratories, 2009. Date Accessed June 7, 2019. `http://operations.fnal.gov/rookie_books/Booster_V4.1.pdf`