Deep Learning for LIGO’s Non-Linear Dynamic Controls

Using Deep Learning to Acquire the Lock

Peter Ma | Supervisor: Dr. Gabriele Vajente

Introduction

What is LIGO?

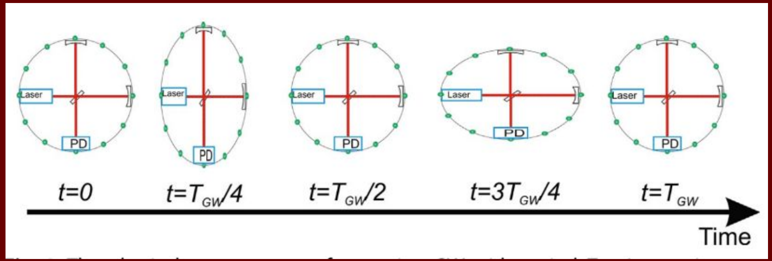
LIGO stands for the Laser Interferometer Gravitational-Wave (GW) Observatory.

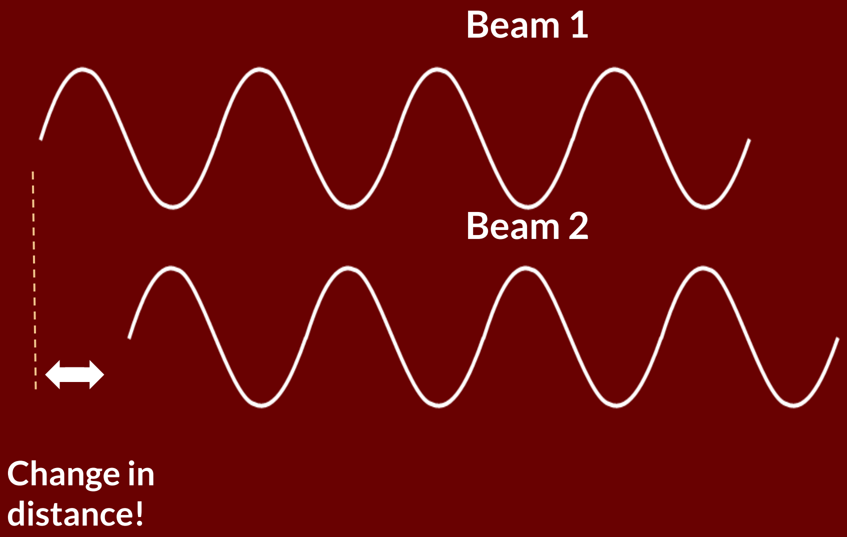
Detects GW from measuring dilation of space.

LIGO measures changes of space by sending two lasers beams down 2 arms which gets reflected then get combined.

The combined beam reveals the changes in path length!

The dimness of the beam is a indication of how far off from being inphase the beam is



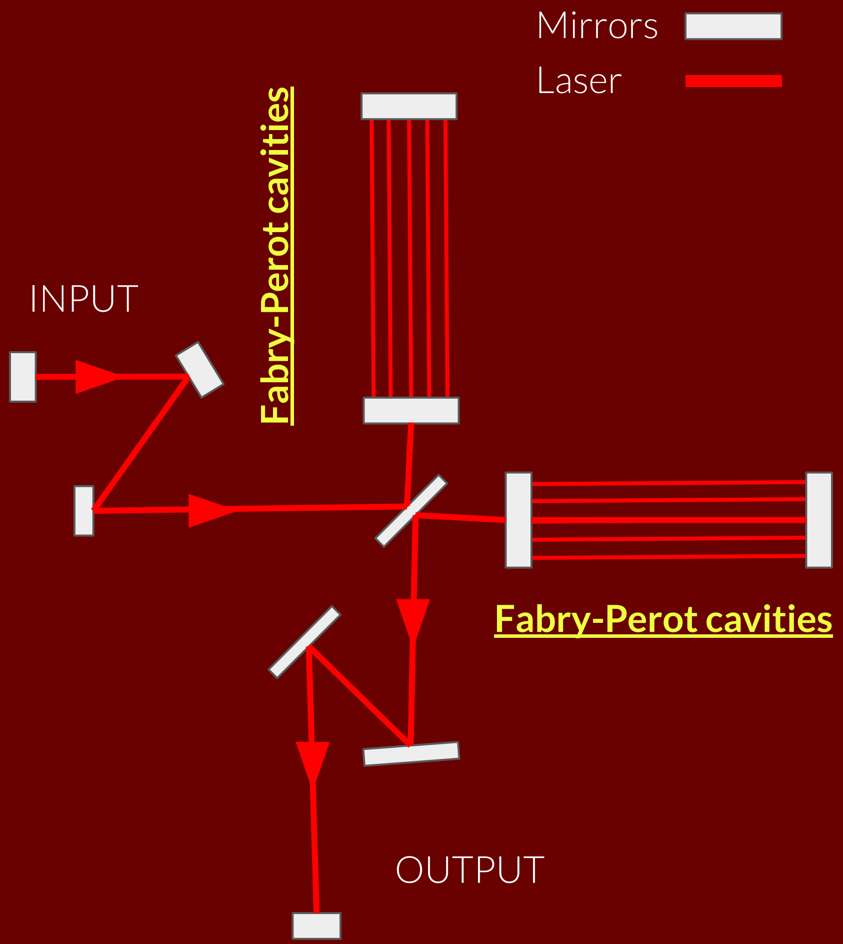


Introduction

LIGO Mirrors

LIGO uses series of important mirrors to amplify the signals from the 50W-90W laser.

One important mirror is the **Fabry-Perot cavities**. The Fabry-Perot cavities are used to recirculate the photons inside the 4km-long arms. So that they accumulate more change in phase for the same displacement of the mirror created by a GW

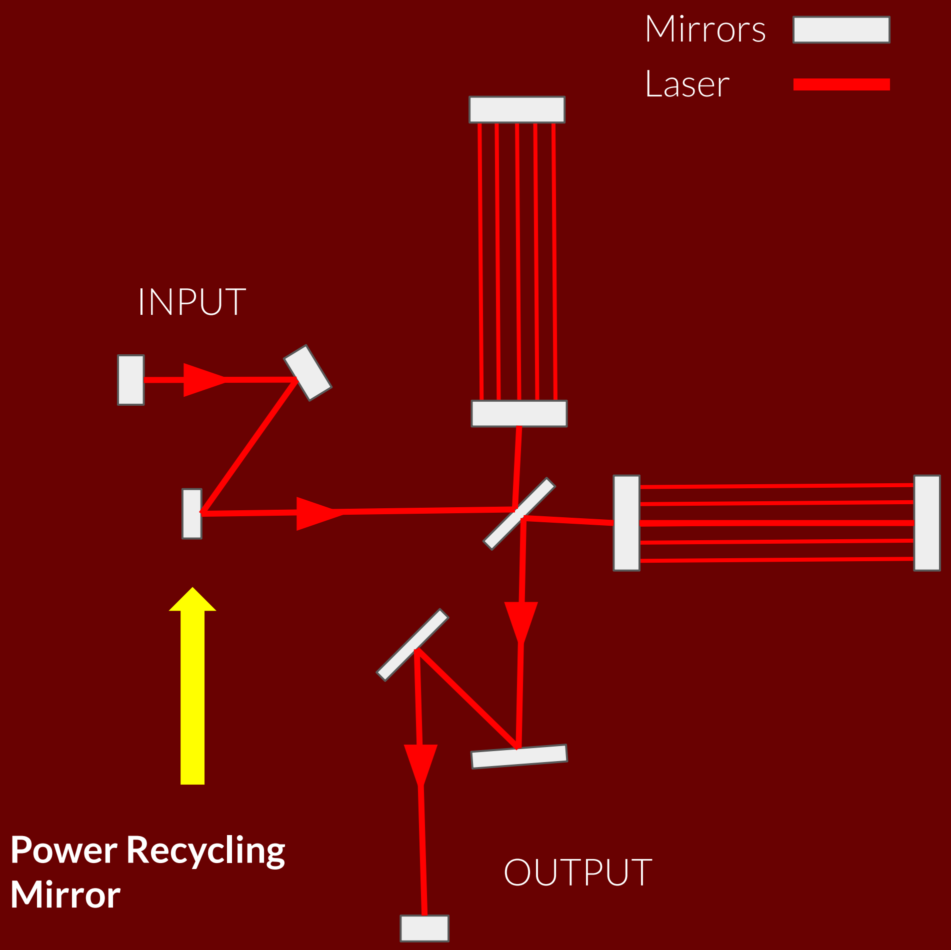


Introduction

LIGO Mirrors

We also have a **Power Recycling Mirror**. The purpose of this is that once tuned to resonance it puts more power through the entire interferometer.

Bounces light back and forth until it turns a 50W laser into something much more powerful.



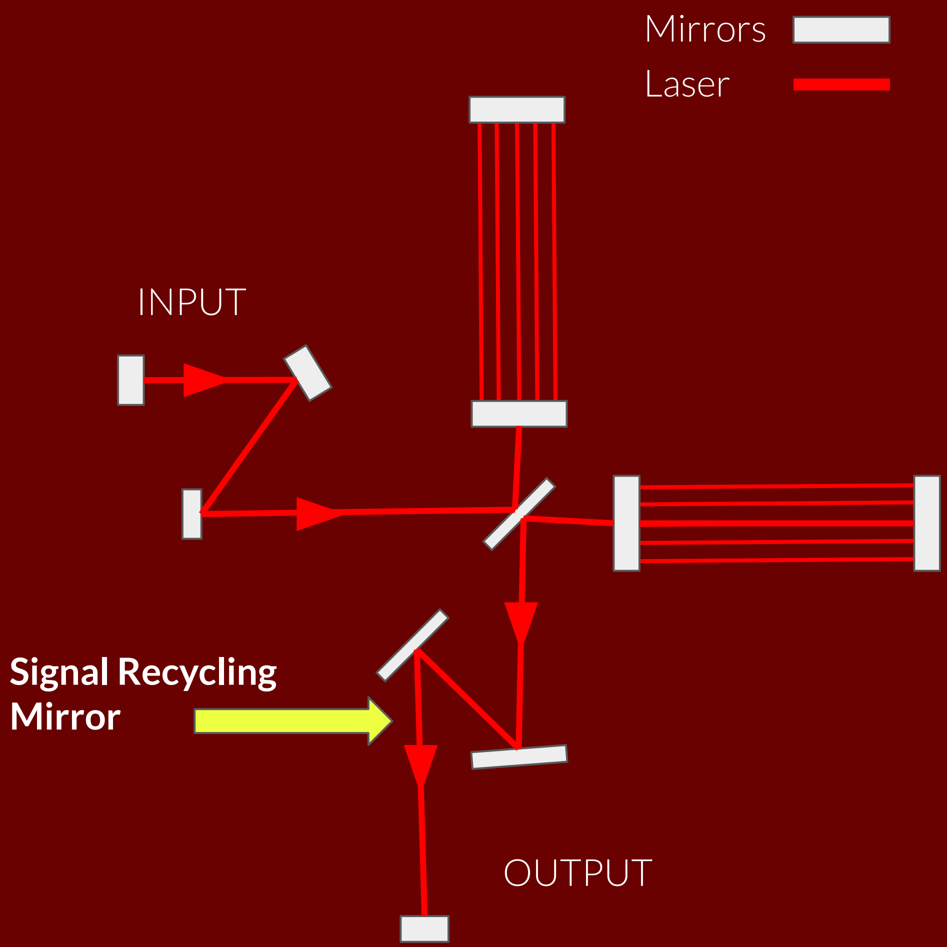
Introduction

LIGO Mirrors

Finally we have **Signal Recycling Mirror**. This part of the mirror is yet another cavity to promote resonance.

Since we know that the GW produces small changes in the phase, there are these side bands. We can choose to amplify the signal amplitude at the price of further reducing the detector bandwidth or increase the detector bandwidth at the price of a small de-amplification of the signal.

These side bands are caused by the potential phase modulation of the signal from the GW, where the GW frequency centered in the middle.



The Problem

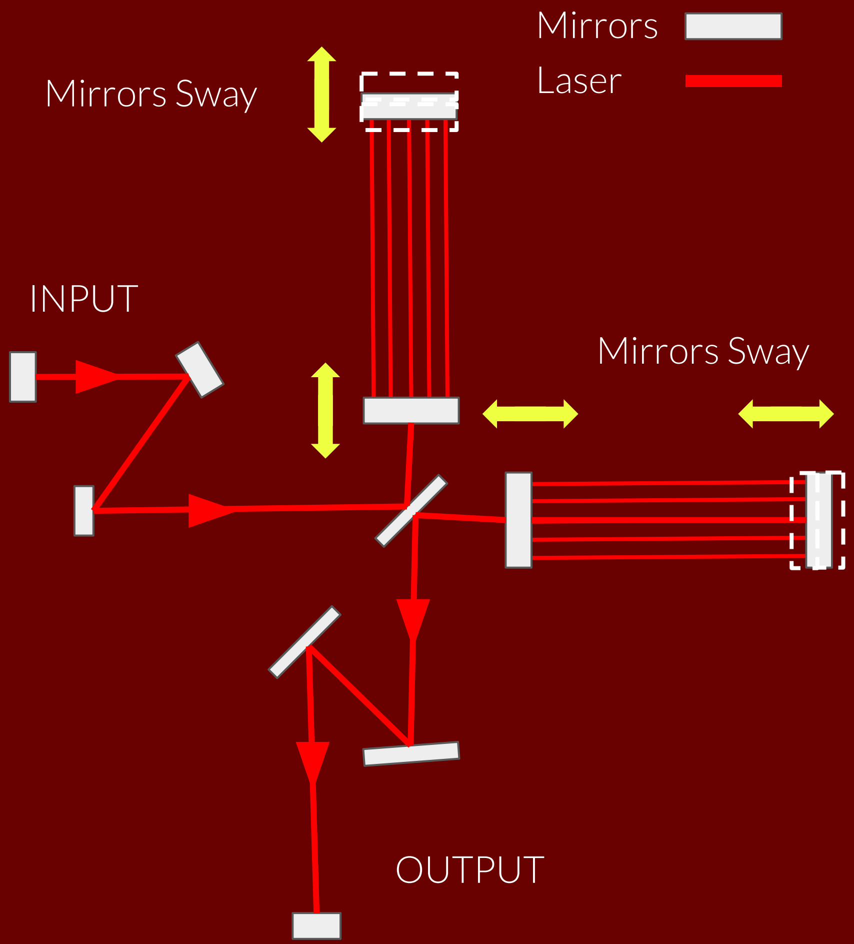
Controlling Mirrors

Due to small motions caused by seismic motion, the mirrors can move.

We care about longitudinal motions. The movement interferes with observation.

Control is solved: If we know position of mirrors => we can control mirrors to stop motion

Problem: We don't know the relative position of Mirrors

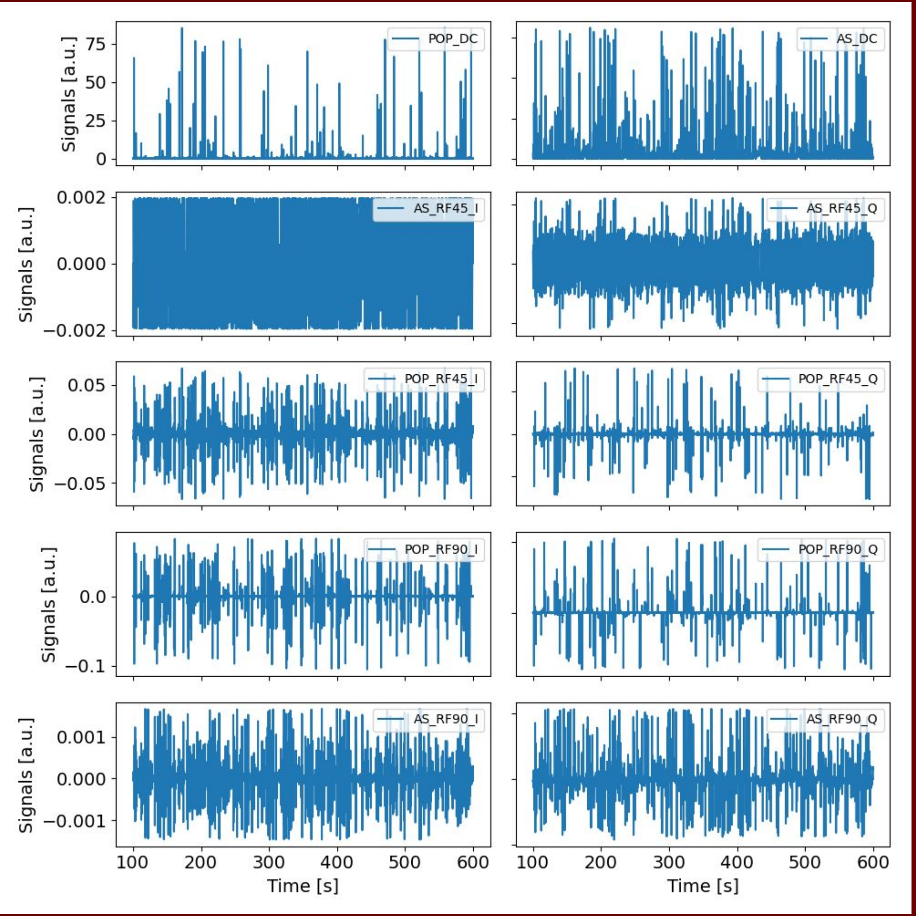


The Problem

Estimating Position

All we do have are these signals that are non-resonant with the cavity (lasers) that run through the mirrors. These signals contain information about the positions of the mirrors, the only issue is that these signals are highly non-linear mappings of the position to the signal power.

We have simulations that go from positions => signal. But we don't have the reverse. The mapping is not globally invertible



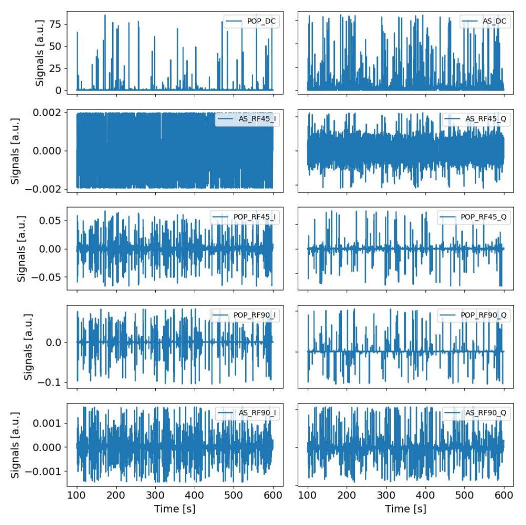
Problem: given the *measured optical signal* (and historical data) can we estimate with reasonable accuracy *the current state of the system?*

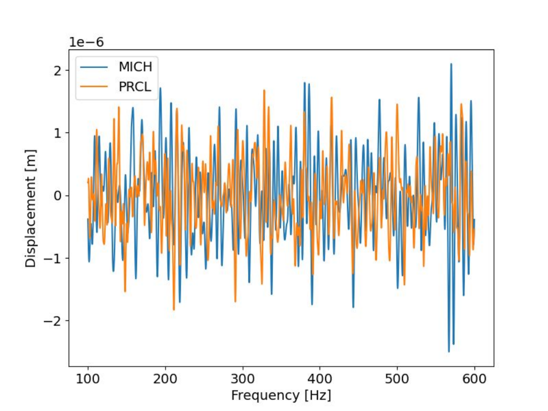
Previous Solution Attempt: We implement a GRU - take in time series data and try to estimate the positions of the mirrors.

The Status Quo
The Data

We choose to work with simulated signals sampled at 2048 Hz (PRMI) or 8192 Hz (FP), and to use 0.25 s of past data, corresponding to 512 (2048) past samples.

We have total of 12 inputs signals in time series and together we want to produce 2 time series in terms of position.





The Status Quo

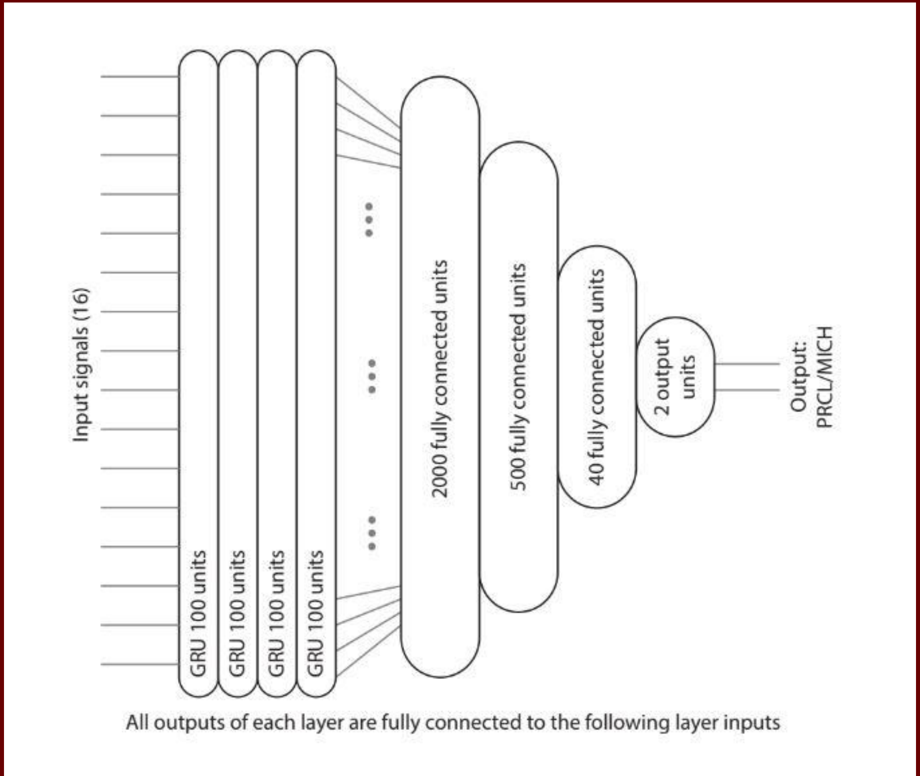
GRU Model

A set of the optical signals is used as the input of a multi-layer recurrent network made of Gated Recurrent Units (GRU).

All input signals are connected to all units in the first layer.

The outputs of the last recurrent layer are connected to the input of a multi-layer fully connected deep network.

ReLU activation functions



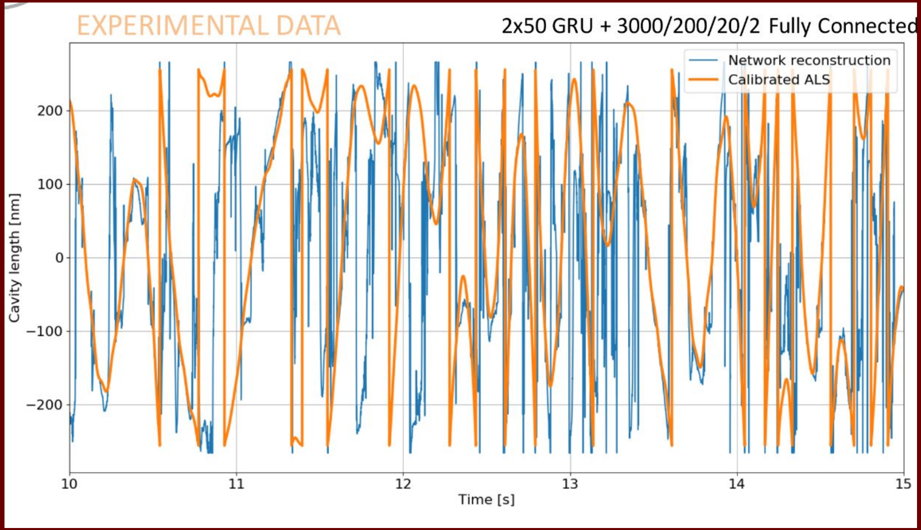
The Status Quo

Why it wasn't enough

One open problem was how to enforce the continuity of the output signals: they at times have big unphysical jumps.

Also the wrapping issue, due to the periodicity in MICH and PRCL.

Every signal is periodic, and so in theory there are infinite solutions for these positions. So to solve this issue we only look at intervals of the data. Issue is these hard intervals introduce discontinuities.



1. **Proposed Solution**: We implement an “online environment”, to train model in supervised way.

The Proposed Solution

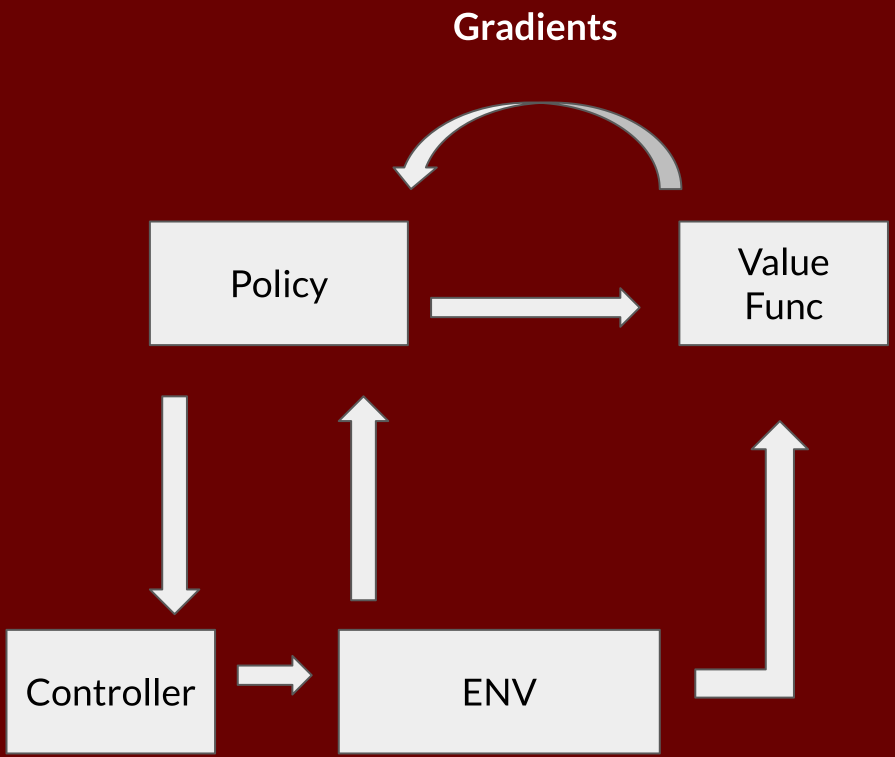
RL Online Learning

“Policy”: We take data sequentially. We feed the data into a simple neural net which produces position estimates.

“Value Function”: We take the simulation and we feed the position estimates into the simulation which produces signal. Take simple MSE between real and simulated.

“Reward”: Take gradients and update Policy network.

Controller: Already Existent



The Proposed Solution

How Does It Solves Problem?

1) Having model “evolving” through time, fits the model locally in time to original function.
   - Instead of having one big model that fits everything we just need a smaller model that fits to small intervals of time.

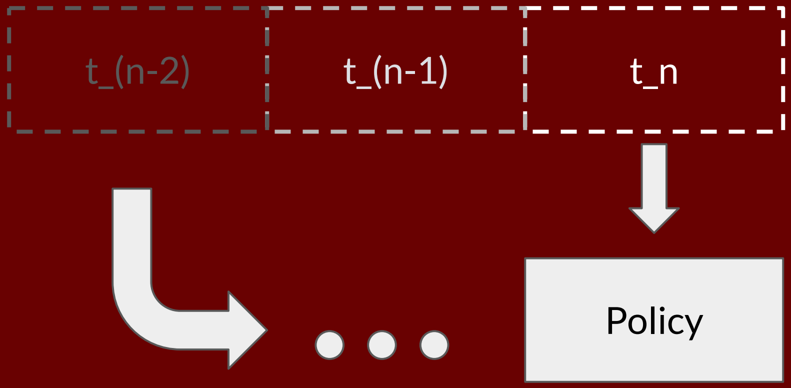
2) We can easily add custom regularizations to control unphysical jumps in the value function. These adapt with time as well.

The Proposed Solution

Potential Roadblocks

1. Memory mechanism
   a. We need to devise a means of passing information from previous snapshots in time series data.

2. Controlling Model Dynamics
   a. If model evolves through time, it's not always guaranteed it will behave nicely. We need to develop “backups”.



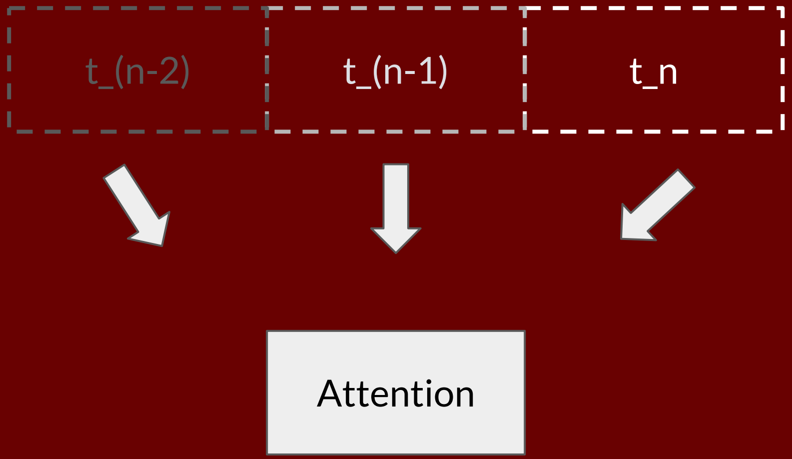
2. **Proposed Solution**: We implement an attention mechanism.

The Proposed Solution

How Does It Solves Problem?

1) Solves potential problems with vanishing gradients and allows us to extend the sequence of data much longer which could help predict positions

2) Attention based models can be made smaller and thus potentially run fast enough for real time.



The Proposed Solution

Potential Roadblocks

1. We still don't have a good way of regularizing continuity

2. The solutions are not unique, and so building a one model fits all might not solve our problems with recreating these states.

Next Steps: Experiment with each approach and benchmark with existing solutions!

Find me at...

Personal Website: Peterma.ca

Email: Peterxy.ma@gmail.com

Twitter: @peterma02

Github: @Petchma

Caltech LIGO UNIVERSITY OF TORONTO