Zara Syed

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SUMMARY

Enthusiastic, creative problem solver, with a figure-it-out mindset, attention to detail and passion for algorithms. Proficient in **Python**, **C/C++**, **Matlab**.

EDUCATION

University of Waterloo

Candidate for BASc, Honors Mechatronics Engineering

Expected Graduation: April 2026
Waterloo, ON

• Relevant Courses: Embedded Systems, Microprocessors, Computer Architecture, Real Time Operating Systems, Data Structures and Algorithms, Circuits, Power Electronics, Controls, Statistics

EXPERIENCE

Base Software Engineering Intern

September 2024 - December 2024

Magna Powertrain

Troy, MI

- Enhanced vehicle software reliability by developing **automated anomaly detection** tool for **CAN traffic**, using **Python**, RegEx, and **CANalyzer** parsing millions of lines of diagnostic data in seconds.
- Revolutionized requirements traceability and achieved 100% audit readiness by **automating requirements linking of 4000 functions** across 10 million lines of C code using **Python, Clang, LLVM,** RegEx, and Excel.
- Automated **SIL** performance evaluation consolidation for customer updates, with 99% task completion time reduction, parsing 130+ HTML Unit Test reports using Python, RegEx, Jenkins, and Excel **saving 8-10 hours each release**.
- Analyzed CPU load contribution of CAN hardware module by conducting in-vehicle tests across maneuvers, software versions, and vehicle types (PHEV and ICE) using **vFlash** and **CANalyzer**.

Software and Controls Algorithms Intern

Jan 2024 – Apr 2024

Magna Powertrain

St. Valentine, Austria

- Developed patent-eligible, **real-time deep learning motor control unit**, as potential replacement for PID control, using **Python**, **Matlab**, **and Simulink**.
- Designed and implemented **reinforcement learning algorithm** and reward-based optimization in custom **Gymnasium** environment for motor control.

Software Engineering Intern

May 2023 – Sept 2023

Magna Mechatronics, Mirrors, & Lighting

Newmarket, ON

 Developed and deployed machine learning web app to advise engineers' automotive material choices by predicting stress-strain curves, using Python, Tensorflow, Flask, SQL, Docker, Azure DevOps, and CI/CD.

Digital Signals Processing Algorithm Developer Intern

Sep 2022 - Dec 2022

ON Semiconductor

Waterloo, ON

- Optimized memory usage by 75% and cycle count by 45% by tracing assembly instructions and exploiting chip architecture, leveraging conditional compilation and cyclical addressing.
- Developed **32-bit fixed-point firmware** functions using **low level C code** for LPDSP32, including signal windowing functions.

Machine Learning Intern

Jan 2022 - Apr 2022

XSENSOR Technology Corporation

Calgary, ON

- Developed Human Pose Estimation (HPE) pipeline which processed 2m+ sensor outputs using **Tensorflow**, **Keras**, **Pandas**, **Numpy**, **and Multiprocessing**.
- Developed 85% accurate Anthropometric meta data extraction based on sensor outputs.
- Built digital filter tuner used to tune FIR parameters to 87% accuracy for biosignal extraction.

PROJECTS

Real Time Operating System | *C, STM32* | GitHub

Dec 2023

• Developed kernel and functionality for thread creation, scheduling, and multithreading.

Autonomous Vehicle Simulation | *Python, Tensorflow*

Jan 2019 – Mar 2019

• Implemented CNN to train simulated self-driving car on Udacity's self-driving car simulator.

Reinforcement Learning: Redefining Motor Control (Article)

Overview

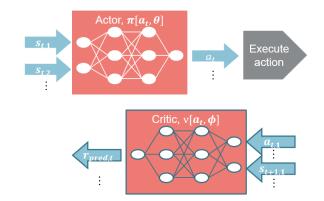
I developed an advanced deep learning solution for motor control systems, simplifying the complexity of traditional model-based control algorithms by replacing them with a single, adaptive reinforcement learning (RL) agent. Using an Actor-Critic Deep Deterministic Policy Gradient (DDPG) method, I trained the RL agent to replicate the functionality of a PID controller. This solution eliminates the need for time-consuming PID tuning while delivering precise, adaptive control across a wide range of operating conditions.

Learning Environment

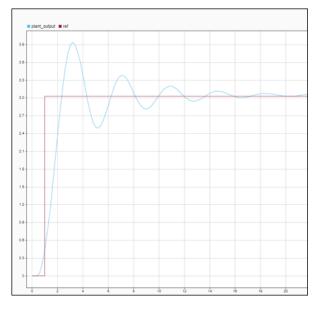
The learning environment is built in Simulink, including a motor, a reference value, and a feedback loop. The motor is modeled by a plant with an arbitrary transfer function. The DDPG algorithm in Python processes real-time simulation data to train the agent. To ensure seamless interaction between Python and Simulink, I implemented a synchronization mechanism that allowed the simulation to run step-bystep, sending data to Python at each step, ensuring a smooth workflow.

Model Training

The learning framework involves 2 neural nets, based in Python: an actor, and a critic. The actor outputs what actions, or control value, it thinks the RL agent should perform in the environment. In Simulink, this action is executed. The updated environment state data is sent back to Python,



Actor-Critic Method



Training Results: Plant Output Approaches Steady-State

where the critic attempts to predict the reward, as it does not have access to the reward function. The actual reward function output is compared to the critic's prediction, and the resultant error is used to advise both networks' updated parameters via backpropagation.

Results and Takeaways

The RL agent was able to reach the reference value. I was really surprised to see that the trained RL agent replicated the exact behavior of a PID controller, without ever having any reference to a PID controller. I also internalized that the reward function design is a strong contributor to the agent's learning!

No Libraries, No Shortcuts: Engineering Backpropagation from Scratch (Github)

Overview

To deeply understand the ins-and-outs of the backpropagation algorithm, I took on the challenge of building and training a neural network completely from scratch, without the use of any machine learning libraries. To demonstrate the application of the algorithm, the model classifies species of iris flowers. An in-depth code and algorithm walk-through is available at my <u>Github</u>.

Model

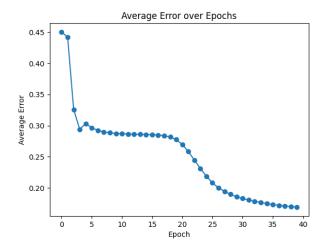
The network had three layers: an input layer, a hidden layer powered by the Leaky ReLU activation function, and an output layer using the Softmax function for probabilistic predictions.

Algorithm

After much literature review to fully understand the back-propagration algorithm, I developed my own implementation, applying calculus concepts including gradients, partial derivatives, and chain rule. The resulting functionality updates the parameters of the model in a "backwards" fashion, hence the name: *backpropagation*. In short, for each prediction of the model, the error is computed with respect to each parameter. Then, a proportional update is made to each parameter. For more details, find my report on my Github repo.



Image From UC Irvine Machine Learning Repository



Training Results: Error Over Time

Results

The maximum accuracy achieved was an impressive 97%, demonstrating a clear drop in error over time, proving the work of the backpropagation algorithm. This experience reinforced my passion for diving deep into complex algorithms and turning theory into results.