CSME 2022 MLC Workshop

Machine Learning Control for Engineering Applications

C. R. Koch / M. Shahbakhti / A. Norouzi

2022-06-06

Workshop Presenters

1. Bob Koch, Professor Mechanical Engineering - ML Overview
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2. Mahdi Shahbakhti, Associate Professor Mechanical Engineering - MPC Overview
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3. Armin Norouzi, PhD Candidate Mechanical Engineering - MLC Implementation
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C. R. (Bob) Koch

Mahdi Shahbakhti

Armin Norouzi

Workshop Overview [1]

Section 1 – Koch

Introduction to Machine Learning for Control – see also [1]

Section 2 – Shahbakhti

Model Predictive Control and Machine Learning Integration

Section 3 – Norouzi

Examples of Machine Learning Control Implementation

[1] References listed at the end

Workshop - Subject Area

Machine Learning Control for Engineering Applications

- Development of control-oriented dynamic models using Machine Learning (ML) techniques.
- Optimal, adaptive and model predictive control techniques that are
- Solved in integration with methods of machine learning including
  - neural networks, deep networks, and reinforcement learning
- Applications in broad linear and nonlinear engineering systems.

Graduate Course - Fall 2022

- MEC E 610 Machine Learning Control for Engineering Applications
- For University of Alberta Graduate students

General Background needed for MLC

Workshop

Only a very brief introduction to ML and MPC

- Motivation to combining MPC and ML
  - Briefly discuss ML, MPC and combining
  - Analysis and design: ideas so try it yourself in Matlab or Python
  - Some further resources for additional information

Helpful Background for Machine Learning Control

1. Undergraduate controls course (or 2) in classical control
2. Modern control
3. Linear algebra - vector spaces, SVD, eigenvalues, etc
4. Undergraduate course in statistics

Workshop Outline

Main Sections

1. Introduction to Machine Learning for Control (Koch)
   1. ML comparison to controls
   2. Methods of combining ML with Model Predictive Control (MPC)
   3. Overview of ML methods needed: ANN, RNN and LSTM, RL
2. MPC and ML integration (Shahbakhti)
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4. Further information and resources for ML

Machine Learning (ML)

- Machine learning is a method of data analysis that automates analytical model building.
- It is a branch of artificial intelligence based on the idea that systems can
  - Learn from data
  - Identify patterns and make decisions with minimal human intervention

Definitions [2]

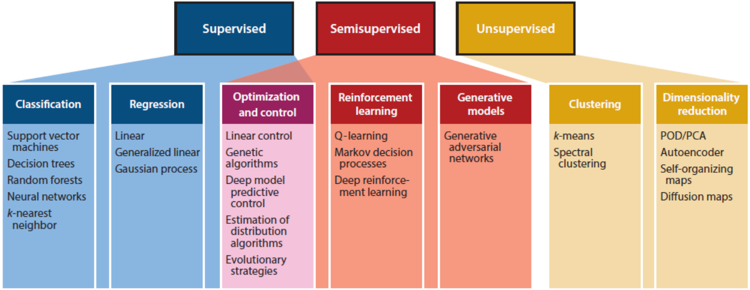
Machine learning algorithms that process and extract information from data; they facilitate automation of tasks and augment human domain knowledge

Supervised learning learning from data labeled with expert knowledge, providing corrective information to the algorithm

Semisupervised learning learning with partially labeled data or by interactions of the machine with its environment (reinforcement learning)

Unsupervised learning learning without labeled training data

Supervised,semi-supervised,unsupervised [2]



PCA - principle component Analysis, POD - proper orthogonal decomposition

Overview of Machine Learning for control

1. Artificial Neural Network (ANN) - models
2. Recurrent Neural Network (RNN) and Long Short Term Memory (LSTM) for sequential inputs
3. Reinforcement Learning (RL) - data driven (model free) control

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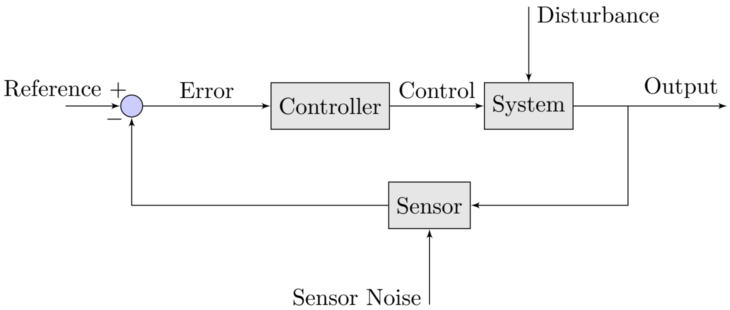
Feedback Control



Advantages

- More robust to **disturbances**
- More robust to **parameter variation**
- Improve **transient response** (stabilize unstable systems)

Disadvantages

- Require a sensor
- System can go unstable

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Why combine MPC and ML for "ML Control"

- Use a model for model based control
  - ML can help MPC
  - MPC can help ML
  - ML can replace the physical model to speed-up calculations for realtime
- Use the large amount of MPC knowledge and combine with ML to improve control
- Physical model and understanding can be used to incorporate "domain knowledge" into the control
- 5 categories below

Machine Learning (ML) and Model Predictive Control (MPC)

1. ML in model structure of MPC:
   - A machine learning-based model, is used to develop a model which is used directly to design MPC or implement optimization based on it
   - Depends on the structure of the learning algorithm, modeling can be done online or adaptive
2. ML in control structure of MPC: ML is combined in the controller structure
   - To enhance MPC structure in terms of stability, optimization accuracy, and computational cost
   - ML can be augmented inside the MPC or as an add-on controller
3. ML in imitation of MPC: In imitation of MPC, ML is used to mimic the MPC controller's behavior in a realtime
   - Can decrease the computation time decreases significantly
   - All optimization is done in the prototype system
   - An approximate function is deployed for the MPC in real-time
   - Depends on the structure of the learning algorithm, modeling can be done online or online.

Machine Learning (ML) and Model Predictive Control (MPC)

4. <u>ML in optimization of MPC</u>: ML methods are used to improve optimization accuracy and computational time
   - This optimization method can be employed in MPC.
5. <u>MPC for safe ML controller</u>: an MPC-based filter is used to guarantee the constraints satisfactory of ML-based controller
   - Pure learning-based algorithms, such as reinforcement learning, do not consider hard systems constraints

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Motivation: ML for dynamic models

Describe when ML can be used for dynamic models

1. Offline learning modeling for MPC
2. Adaptive learning modeling for MPC
3. Disturbance and model mismatch

Main Modeling Methods

1. Artificial Neural Networks
    1. Shallow Neural Networks (SNN) and Nonlinear AutoRegressive eXogenous (NARX)
    2. Recurrent Neural Network (RNN) modeling, Long Short-Term Memory (LSTM)
    3. Deep Neural Networks (DNN)
2. Other ML approaches for System Identification (SI)
    1. Support Vector Machine (SVM)
    2. Regression Trees (RT) and Random Forest (RF)
    3. Gaussian Process Regression (GPRs)

Artificial Neural Network (ANN)

- A set of algorithms that try to distinguish the correlation between a set of data using rules thought to mimic human brain operation [3].
- An ANN includes simulated neurons where each node connects to other nodes in neurons through connections that match biological axon-synapse-dendrite joints.

Artificial Neural Network (ANN) Structure

- Each link has a weight, which manages the strength of one node's influence on another.
- The neurons are usually organized into multiple layers.
- The nodes that receive external data as input are the input layer;
  - the output layer produces the predicted output data.
  - In the middle, hidden layers exist between the input layer and output layer that can be varied in size and structure.

Artificial Neural Network (ANN) Schematic

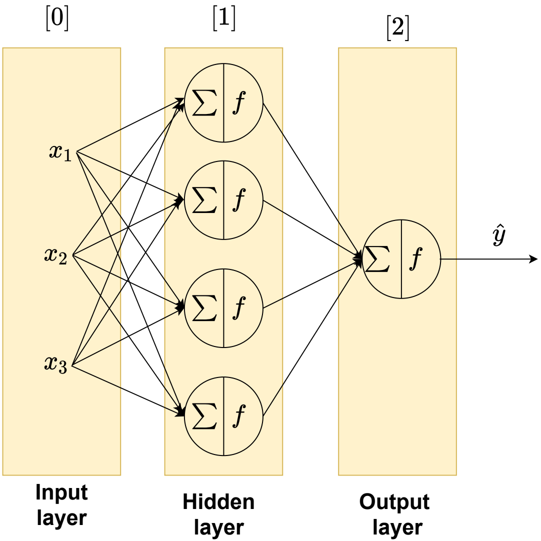


Figure: ANN Schematic of two layer ANN (one-hidden layer ANN) including three main layer

ANN Activation function $f(z)$

- for ANN, the activation function of a node defines the output of that node given an input or set of inputs
- However, only nonlinear activation functions allow ANN to give complex outputs using only a small number of nodes

Common examples

- Sigmoid activation function: $\sigma(z) = \frac{1}{1+e^{-z}}$
- Hyperbolic tangent: $\tanh(z) = \frac{e^z - e^{-z}}{e^z + e^{-z}}$
- Rectified linear unit: ReLU: 0 if $z \leq 0, \quad z$ if $z > 0$

Gradient Decent (GD) for Neural Network

- the cost function is defined as

$$J(W^{[1]}, b^{[1]}, W^{[2]}, b^{[2]}) = \frac{1}{m}\sum_{i=1}^{m} L(\hat{Y}, Y)$$

- where $L(\hat{y}, y)$ is the loss function

  regression usually Mean Squared Error
  classification usually logistic regression

- the cost function can also have regularization

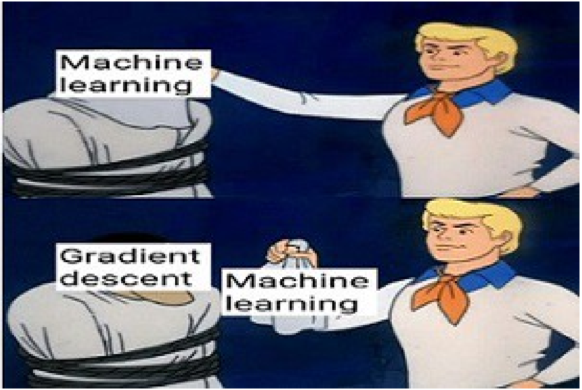
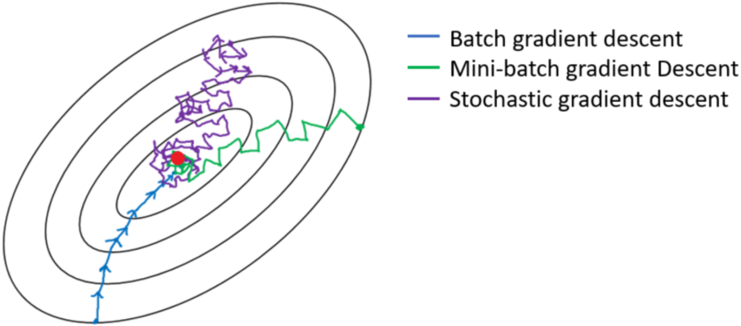


Figure: Machine Learning behind the scenes [4]

Gradient Descent Comparison: Batch, Stochastic and mini-Batch

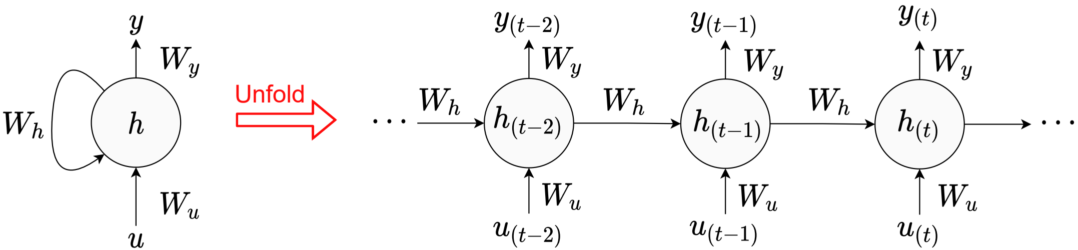
Gradient descent is used to train our model through back propagation

1. Batch Gradient Descent - all the data per step - local minimum
2. Mini Batch Gradient Descent - part of the data
3. Stochastic Gradient Descent - one data point at a time but slow



The Recurrent Neural Network (RNN)

- Has a similar structure to a feedforward ANN
- Has backward connections that are used to handle sequential inputs [6].
- The simplest RNN for time step t is shown in the Figure
- This recurrent neuron receives both inputs $u(t)$ and output from the previous time step, $y(t-1)$.
- The output of the first step is generally initialized as zero.
- The structure of RNN can be revealed by unrolling it in time, see Figure [6].
- The output of the recurrent neuron at the current time step t is a function of past inputs, so a recurrent neuron can be considered a memory [6].



RNN disadvantages are:

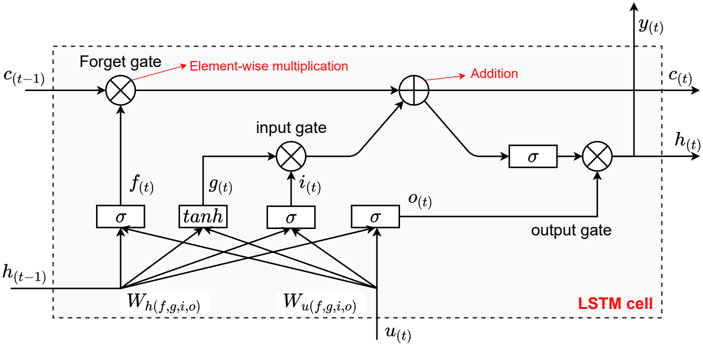
- Cannot capture long-term dependencies since RNN prediction is based on recent steps.
- RNN also suffers from "vanishing gradient", which means that
  - The contribution of earlier steps becomes increasingly small in the RNN gradient.
  - This ignores long-term dependencies during training.
- So various types of cells with long-term memory were introduced to tackle this problem.
  - The most popular and well-known of these long-term memory cells is the Long Short-Term Memory cell (LSTM).

Long Short-Term Memory (LSTM)

- when LSTM is compared to RNN, in LSTM the hidden state is split into two main part:
  - $h_{(t)}$ the short-term state, and $c_{(t)}$ the long-term state.

Long Short-Term Memory (LSTM)

- $h_{(t)}$ the short-term state, and $c_{(t)}$ the long-term state.
- The long-term state $c_{(t-1)}$ traverses the network from left to right.
  1. this state first enters the forget gate where past values are dropped
  2. then some values (memories) are added to the input gate to get c_t
  3. so at each time step, some memory is added, and some are dropped, and
  4. the current long-term state $c_{(t)}$ is output without further change.



Deep Neural Network (DNN)

- DNN using Fully Connected (FC) network often use a shallow neural network for modeling
- RNN to model dynamic of system for MPC application

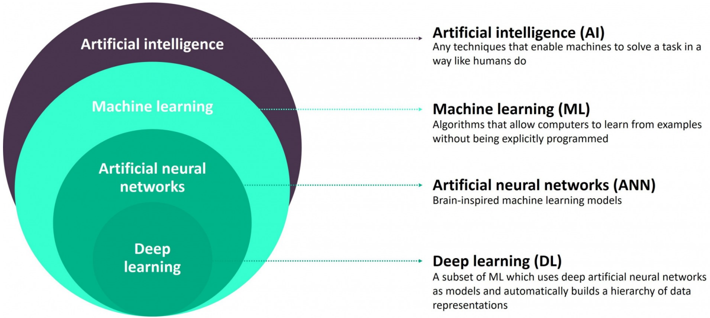
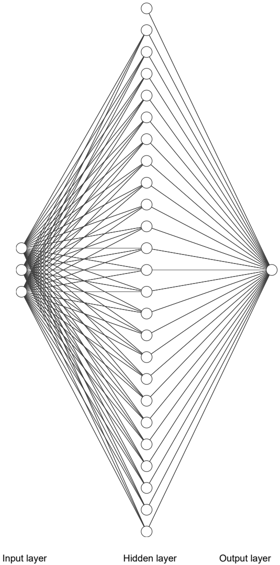


Figure: AI hierarchy with deep learning [7]

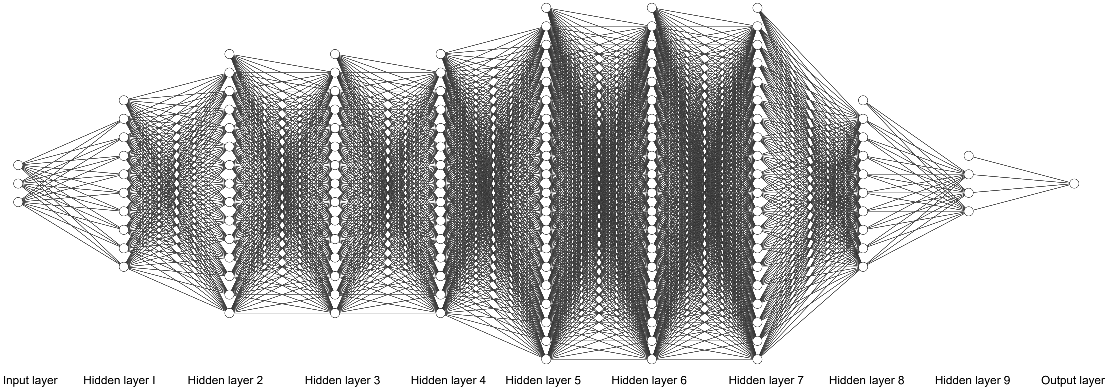
Deep Learning (DL) is a subset of ML

- DL uses a deep ANN as model (DNN) to automatically build a hierarchy of data representation – see Figure below
- So far the neural networks considered had one or two hidden layer
  - these are called shallow neural network
- To model complex systems, we need more learn parameter in our model. To do this we have two main options:
  1. A shallow network that has a low number of hidden layers.
     - While there are studies that a shallow network can fit any function [6]
     - it will need to be really tall - this causes a large increase in the number of parameters
  2. A deep network (wide) has been found to fit functions better with less parameters than a shallow network (tall) [6]

Example of Tall (shallow) Deep Neural Network (DNN)



Example of Wide Deep Neural Network (DNN)



Deep Neural Network (DNN) and CNN

- For example a deep network with 5 layers and 10 neurons in each layer may work more efficient than a single hidden layer network (shallow NN) with 1000 neurons.
- Broad application of DNN using Recurrent Neural Networks (RNNs) in which data can flow in any direction, such as language modeling and deep Convolutional Neural Networks (CNNs) which are used in computer vision.

DNN Advantages and Challenges

- DNN has advantages discussed above

Challenges of DNN:

1. related to training a much deeper ANN - many layers can have hundreds of neurons linked by hundreds of thousands of connections.
2. Vanishing and exploding gradients:
   - This is when the gradients grow smaller and smaller or larger and larger
   - when flowing backward through the DNN during training
   - Both vanishing and exploding gradients make lower layers very hard to train.
3. Not enough training data
4. Training may be extremely slow
5. A model with millions of parameters
   - at risk of severely overfitting the training set
   - especially if there are not enough training instances or if they are too noisy.

DNN Training Techniques

Vanishing/Exploding Gradients Solutions

- The signal must flow properly in both directions:
  - **Initialize** the variance of the outputs of each layer needs to be equal to the variance of its inputs,
  - in addition, need the gradients to have equal variance before and after flowing through a layer in the reverse direction.
- **activation function** needs to be a non-saturating function
- **Batch normalization** - scale and shift for each layer

Faster Optimizers

- can speed up with: Initialization strategy, proper activation function, Batch normalization

To significantly boost training speed use:

a faster optimizer than the regular Gradient Descent optimizer. Such as:

1. Gradient Descent With Momentum
2. Root Mean Squared Propagation (RMSProp)
3. Adam optimizer are used

Gradient Descent With Momentum

Gradient descent problems

- bounces around the search space when
  - optimization problems that have large amounts of curvature or noisy gradients,
- can get stuck in flat spots in the search space that have no gradient.

Momentum is an extension to GD optimization algorithm to allow

- the search to build inertia in a direction in the search space
- overcome the oscillations of noisy gradients
- "coast" across flat spots of the search space.

The Algorithm

- accumulates moving average of past gradients and move in that direction,
- while exponentially decaying.

The Momentum method accelerates learning, when:

- Facing high curvature
- Small but consistent gradients
- Noisy gradients
- Examples of optimizers come later

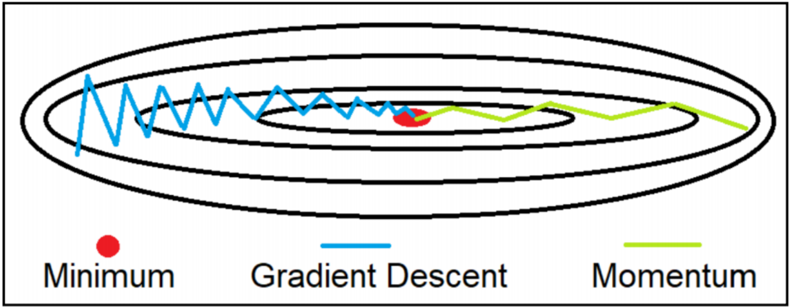


Figure: Gradient Descent vs Gradient Descent With Momentum [8]

Root Mean Squared Propagation, or RMSProp

RMSProp, is an extension of gradient descent that

- uses a decaying average of partial gradients in the adaptation of the step size for each parameter
- uses a decaying moving average allows the algorithm to forget early gradients
- focuses on the most recently observed partial gradients seen during the progress of the search.

Adam Optimization (adaptive moment estimation)

Adam combines the ideas of momentum optimization and RMSProp

- just like momentum optimization, it keeps track of an exponentially decaying average of past gradients
- just like RMSProp, it keeps track of an exponentially decaying average of past squared gradients.

RT implementation of LSTM-NMPC: Model in/outputs [2]

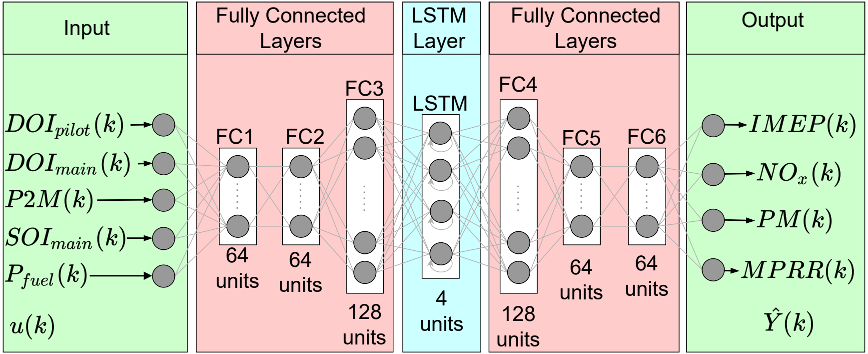


Figure: Structure of proposed deep neural network model for engine performance and emission modeling. LSTM: Long-short term memory, SOI: start of injection, DOI: duration of injection, P_{fuel}: fuel rail pressure, IMEP: indicated mean effective pressure, MPRR: Maximum pressure rise rate, PM: particle matter, t_{P2M}: duration between end of pilot injection and start of main injection

[2] Deep Learning and Nonlinear Model Predictive Control Integration for Compression Ignition Engine Emission Reduction, Norouzi,Shahpouri, Gordon, (Winkler,Nuss Andert RWTH), Shahbakhti, Koch: Monday 12:00

RT implementation of LSTM-NMPC- schematic

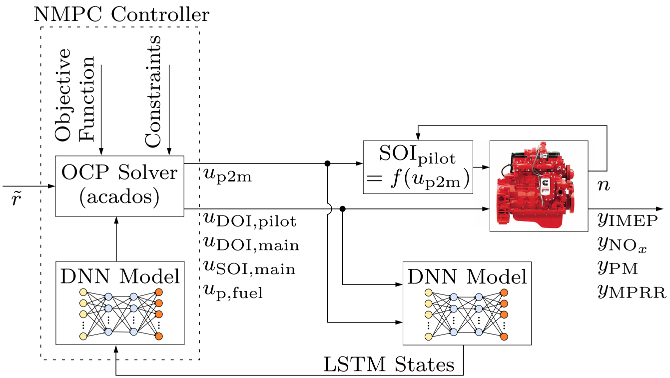
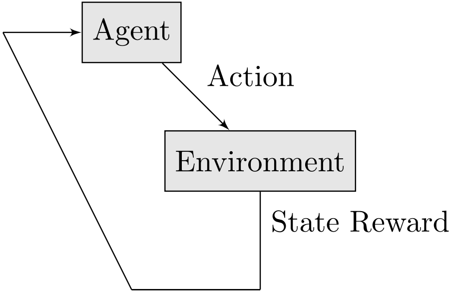


Figure: Block diagram of LSTM-NMPC structure– IMEP: Indicated mean effective pressure, NO_x: Nitrogen Oxide, PM: Particle matter, MPRR: Maximum pressure rise rate, *n*:Engine speed, DOI: Duration of injection, SOI: Start of injection

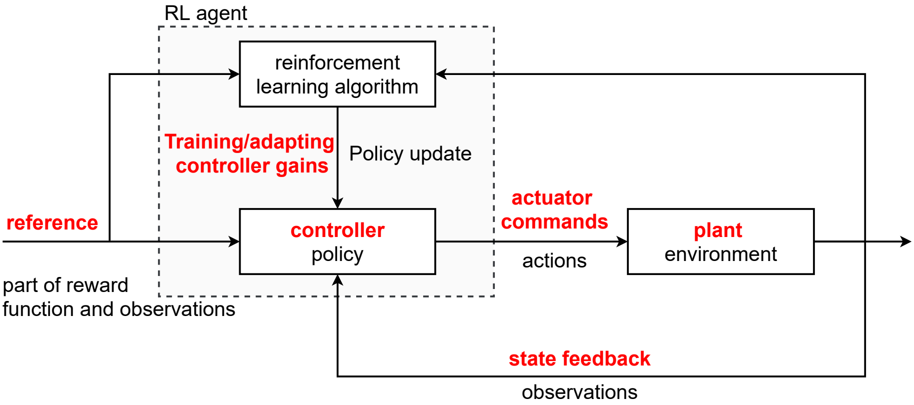
Reinforcement Learning

Reinforcement Learning (RL) is

- one of the most exciting fields of Machine Learning today
- also one of the oldest since it has been around since the 1950s
- some interesting applications over the years
  - particularly in games (e.g., TD-Gammon, a Backgammon-playing program)
  - in machine control, but not as publicized in the common press



Reinforcement learning compared to controls



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RL Concept

- Often, many trials needed. RL for highly constrained engineering systems?[9] [3]

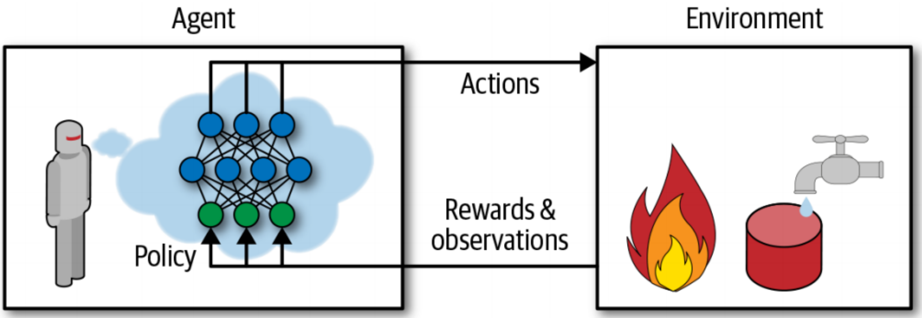
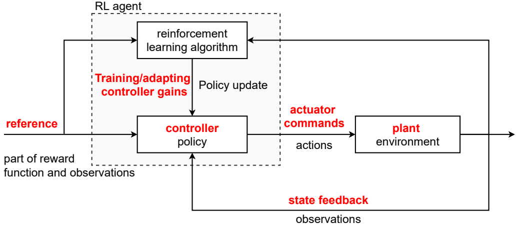
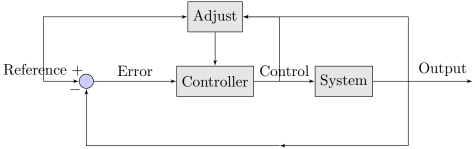


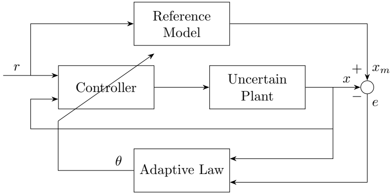
Figure: Reinforcement Learning using a neural network policy

[3] Sutton, RL book Chap 9, One of the most pressing areas for future reinforcement learning research is to adapt and extend methods developed in control engineering with the goal of making it acceptably safe to fully embed reinforcement learning agents into physical environments

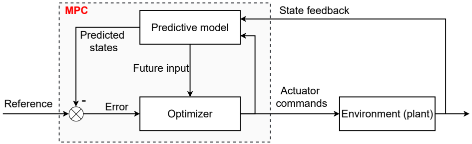
RL compared to feedback control - similar structure



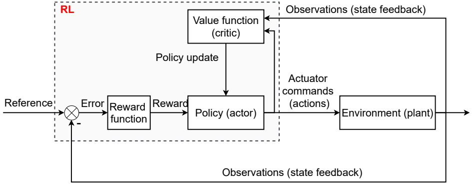




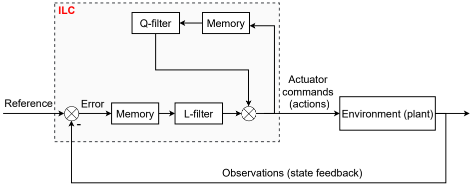
(a) Model Predictive Control (MPC)



(b) Reinforcement Learning (RL)



(c) Iterative Learning Control (ILC)



Workshop Outline Part 2 - Presentation - Shahbakhti

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Workshop Outline Part 3 - Presentation - Norouzi

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Workshop Outline Part 4 - Presentation - Further Resources

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Computer tools

Matlab

- very powerful software for controls
- also good for ML

Python

- open source and very good for ML
- not as good for control
- can Jupyter Notebooks
  - install on your machine (Anaconda)
  - run in a Web Browser: Google Colab
  - many Universities have a Jupyter portal, for example UAlberta

Online Courses - ML - Intro

1. Machine Learning by Stanford University

- Link: Coursera
- Level: Machine learning mathematics included **Good for understanding insight of machine Learning**
- Language: Octave or Matlab

2. Python: 2020 Complete Python Bootcamp: From Zero to Hero in Python

- Link: Udemy
- Level: Elementary to advanced level
- Language: Python

Online Courses - ML - Implement and RL

3. Machine Learning with Python by IBM

- Link: Coursera
- Level: **The best and easiest course to start implementing machine learning** (mathematics behind the machine learning are not included)
- Language: Python

4. Reinforcement Learning Specialization by University of Alberta and Alberta Machine Intelligence Institute (AMII)

- Link: Coursera
  - Fundamentals of Reinforcement Learning
  - Sample-based Learning Methods
  - Prediction and Control with Function Approximation
  - A Complete Reinforcement Learning System (Capstone)
- Deep mathematics of algorithm have been covered based on RL reference Book [9] - **Good for understanding insight of RL**

Online Courses - Deep Learning

5. Deep Learning Specialization by deeplearning.ai

- Link: Coursera
  - Neural Networks and Deep Learning
  - Improving Deep Neural Networks: Hyperparameter tuning, Regularization and Optimization
  - Structuring Machine Learning Projects
  - Convolutional Neural Networks
  - Sequence Models
- Language: Python and in TensorFlow

Online Courses - RL - Matlab and Data Science

6. Reinforcement Learning Toolbox User's Guide by Matlab

- Link: MathWorks
- Level: Includes some examples in Matlab- requirements: 1 and 4
- Language: Matlab

7. IBM Data Science Professional Certificate

- Link: Coursera
  - What is Data Science?
  - Tools for Data Science
  - Data Science Methodology
  - Python for Data Science and AI
  - Databases and SQL for Data Science
  - Data Analysis with Python
  - Data Visualization with Python
  - Machine Learning with Python (4 above)
  - Applied Data Science Capstone

Possible online resources - summary

Extra Information about ML - Possible Study Plan

- If Machine Learning and Python are new for you, you should start from 1 and 2
- If you know machine learning but want to implement ML in Python, you should start from 3
- If your are interested in RL and Deep Learning, you should take 4 and 5
- If you know about RL and you want to implement RL Matlab, you should check out 6
- If your are interested in Data science, you should take 7

[1] Steven L. Brunton and J. Nathan Kutz. *Data-Driven Science and Engineering: Machine Learning, Dynamical Systems, and Control*. Cambridge University Press, 2019. DOI: 10.1017/9781108380690.

[2] Steven L. Brunton, Bernd R. Noack, and Petros Koumoutsakos. "Machine Learning for Fluid Mechanics". In: *Annual Review of Fluid Mechanics* 52.1 (Jan. 2020), pp. 477–508. DOI: 10.1146/annurev-fluid-010719-060214.

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The momentum update rule (recursive) - details

The momentum update rule is, for $\ell = 1, \ldots, l$;

$$\begin{cases} v_{dW^{[\ell]}} := \beta v_{dW^{[\ell]}} + (1-\beta) dW^{[\ell]} \\ W^{[\ell]} := W^{[\ell]} - \alpha v_{dW^{[\ell]}} \end{cases}$$

$$\begin{cases} v_{db^{[\ell]}} := \beta v_{db^{[\ell]}} + (1-\beta) db^{[\ell]} \\ b^{[\ell]} := b^{[\ell]} - \alpha v_{db^{[\ell]}} \end{cases}$$

- $dW^{[\ell]}$ is $\frac{\partial L}{\partial W^{[\ell]}}$ and $db^{[\ell]}$ is $\frac{\partial L}{\partial b^{[\ell]}}$
- where l is the number of layers, β is the momentum and α is the learning rate.
- A new hyperparameter β, called the momentum
  - must be set between 0 (high friction) and 1 (no friction)
  - a typical momentum value is 0.9

RMSProp update rule (recursive) - details

- The parameter update rule for RMSProp is

$$\begin{cases} s_{dW^{[\ell]}} := \beta_2 s_{dW^{[\ell]}} + (1-\beta_2) dW^{[\ell]} \odot dW^{[\ell]} \\ W^{[\ell]} := W^{[\ell]} - \alpha \frac{dW^{[\ell]}}{\sqrt{s_{dW^{[\ell]}} + \epsilon}} \end{cases}$$

$$\begin{cases} s_{db^{[\ell]}} := \beta_2 s_{db^{[\ell]}} + (1-\beta_2) db^{[\ell]} \odot db^{[\ell]} \\ W^{[\ell]} := W^{[\ell]} - \alpha \frac{db^{[\ell]}}{\sqrt{s_{dW^{[\ell]}} + \epsilon}} \end{cases}$$

- ϵ is hyperparameter preventing division by zero
- β_2 Exponential decay hyperparameter for the moment estimates. β_2 is usually 0.9.
- Except on very simple problems
  - this optimizer almost always performs much better than GD
  - it was the preferred optimization algorithm of many researchers until Adam optimization became prevalent

Adam Optimization- details

The general update rule for Adam (recursive) is, for $\ell = 1, \ldots, l$:

$$\begin{cases} v_{db^{[\ell]}} := \beta_1 v_{db^{[\ell]}} + (1-\beta_1) db^{[\ell]} \\ v^{corrected}_{db^{[\ell]}} := \frac{v_{db^{[\ell]}}}{1-(\beta_1)^t} \\ s_{db^{[\ell]}} := \beta_2 s_{db^{[\ell]}} + (1-\beta_2)(db^{[\ell]} \odot db^{[\ell]}) \\ s^{corrected}_{db^{[\ell]}} := \frac{s_{db^{[\ell]}}}{1-(\beta_2)^t} \\ b^{[\ell]} := b^{[\ell]} - \alpha \frac{v^{corrected}_{db^{[\ell]}}}{\sqrt{s^{corrected}_{db^{[\ell]}}}+\varepsilon} \end{cases}$$

- β_1: exponential decay hyperparameter for the first moment estimates
- β_2: exponential decay hyperparameter for the second moment estimates,
- ϵ hyperparameter preventing division by zero in Adam updates.
- v: moving average of the first gradient in the Adam rule
- s: moving average of the squared gradient in the Adam rule
- for initial values can choose $\beta_1 = 0.9$, $\beta_2 = 0.999$, $\epsilon = 10^{-7}$, and $\alpha = 0.001$.

Combined ML and MPC from applications

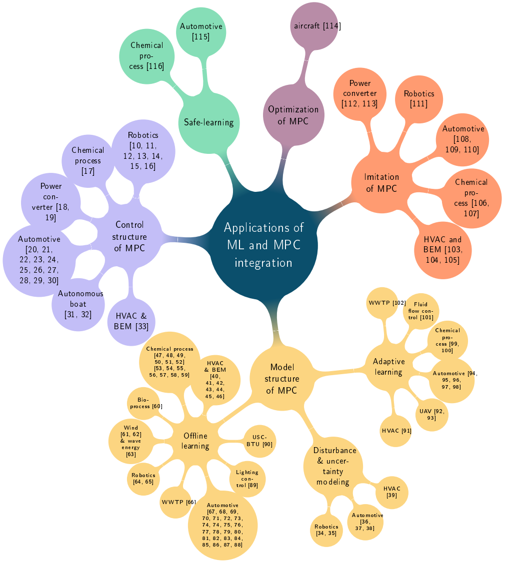

Figure: Applications of AI and MPC integration overview