Development of Neural Network Based Control Systems and Optimization Tools for Accelerators: A Very Brief Introduction

Auralee Morin - graduate student
Sandra Biedron, Stephen Milton - PIs

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Electrical & Computer
ENGINEERING

Colorado State University

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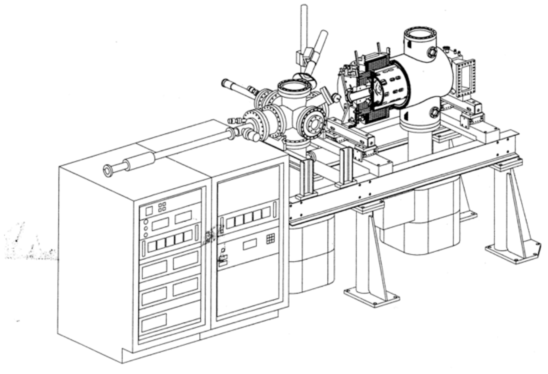
RF Frequency	1.3 GHz
Shunt Impedance	50 MΩ/m
Q-Value	18,000
Axial Electric Field	
Cell no. 1	26 MV/m
Cell No. 2	14.4 MV/m
Cell No. 3 – 6	10.6 MV/m
Solenoid Field Strength	1,200 G



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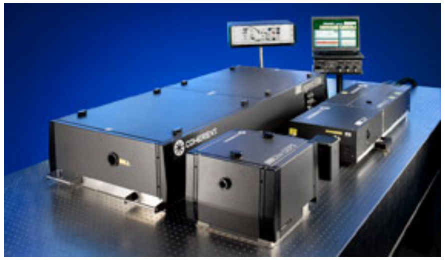

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- Current status: working on equipment/ lab buildup and preparing to move into new building

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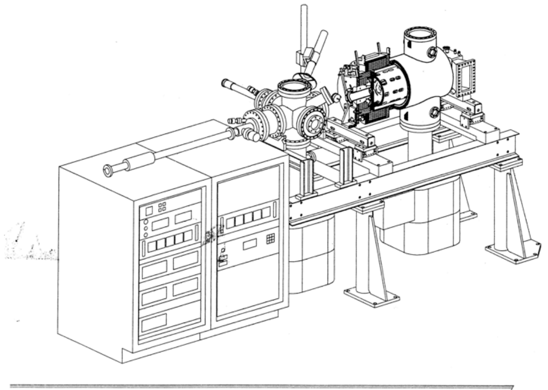

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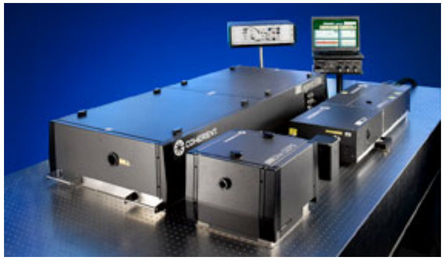

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- Will be used for basic beam research and development (laser, particle, and combined beams)

Background: ABL Basic Layout and Initial Capabilities

Laser Lab 1

100-150 Terawatt Ti:Sapphire laser system.
Wavelength: 0.8 micrometers, Energy before compression: 13 Joules.
Repetition rate: up to 5 Hz.
Plans to scale to 0.5 Petawatt

Laser Lab 2

1 J, 5 picosecond, 100 Hz repetition rate diode-pumped laser (100 W average power)
Wavelength: 1.03 micrometers. Highest repetition rate diode-pumped chirped-pulse-amplification laser in the world. Can be scaled in repetition rate and pulse energy, future parameters depend on funding.

Accelerator Lab

6 MeV Photocathode Driven Electron Linac
L- Band (1.3 GHz)
Two Klystrons Available (One needed for PC Gun)
15 us pulse durations at 10 Hz
Up to 81.25 MHz pulse rates available

Drive Laser Laboratory

Accelerator Control Room

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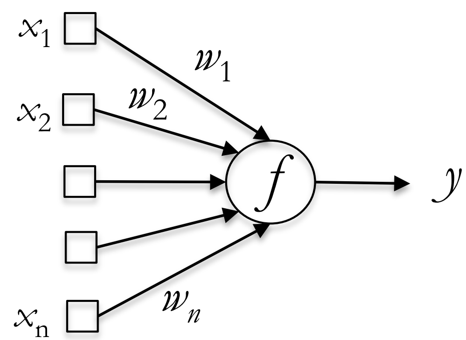

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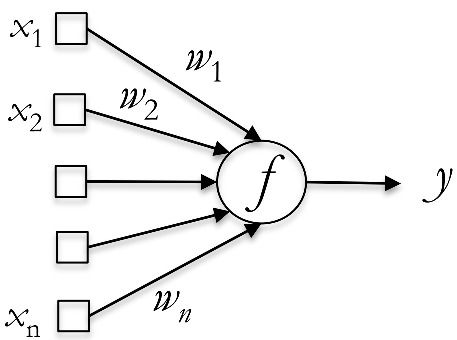

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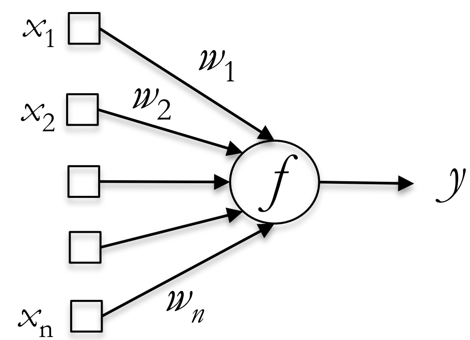

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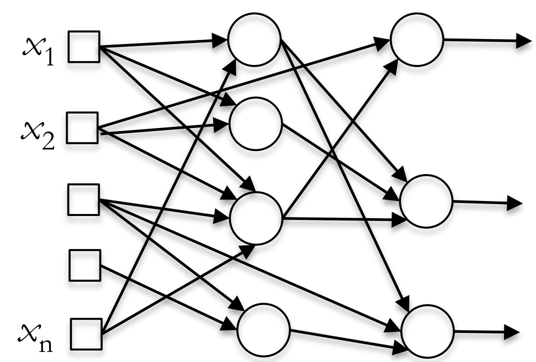

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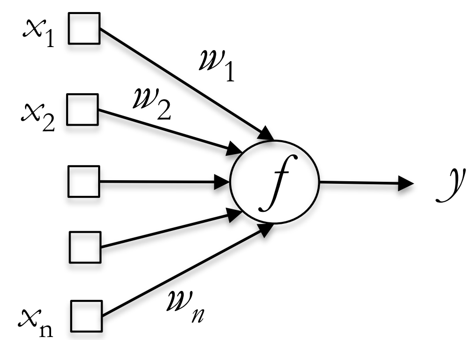
  - Direct terms
  - Individual node biases
  - Number of hidden layers
  - Number of nodes per hidden layer
  - Number of output nodes
  - Overall flow of data: recurrent or feed-forward



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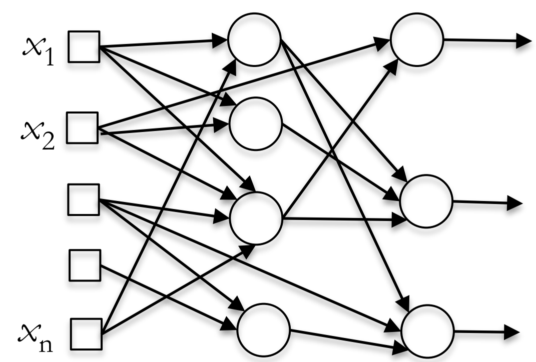

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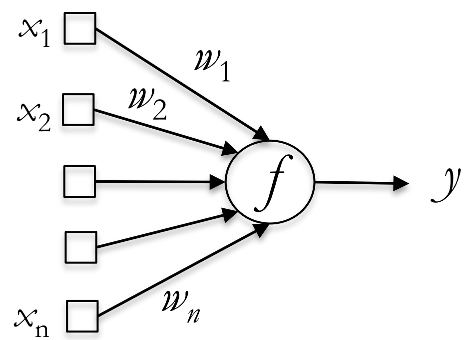

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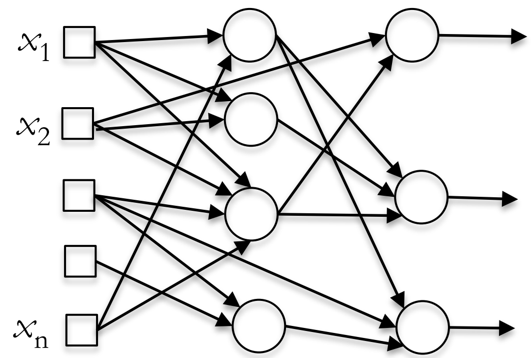

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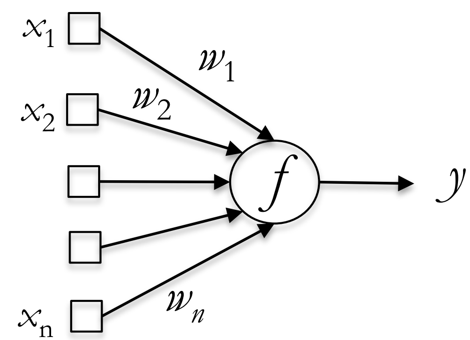

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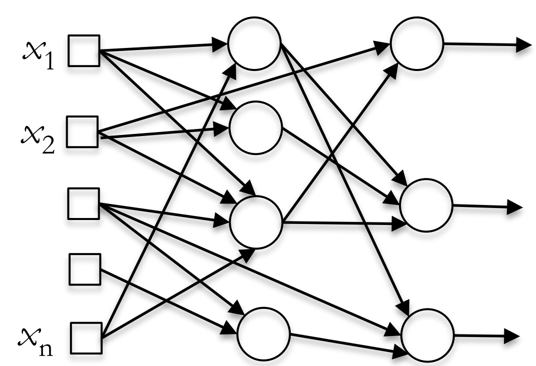

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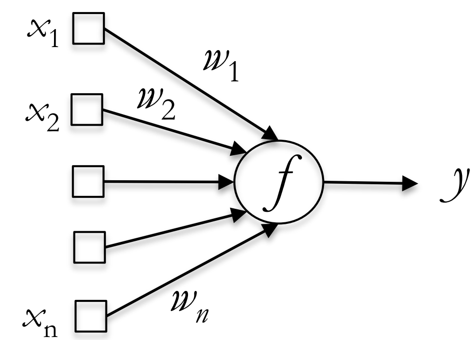
  - → *Essentially, this is an optimization problem involving minimization of the error between the model output and the data*



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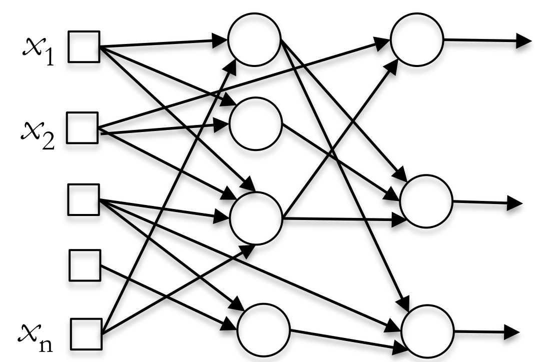

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- Adaptive modeling of systems which show slow changes over time scales longer than the one of primary interest

Neural Networks, Vol. 2, pp. 359–366, 1989

0893-6080/89 $3.00 + .00

ORIGINAL CONTRIBUTION

Multilayer Feedforward Networks are Universal Approximators

KURT HORNIK

Technische Universität Wien

MAXWELL STINCHCOMBE AND HALBERT WHITE

University of California, San Diego

(Received 16 September 1988; revised and accepted 9 March 1989)

Abstract—*This paper rigorously establishes that standard multilayer feedforward networks with as few as one hidden layer using arbitrary squashing functions are capable of approximating any Borel measurable function from one finite dimensional space to another to any desired degree of accuracy, provided sufficiently many hidden units are available. In this sense, multilayer feedforward networks are a class of universal approximators.*

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Why are neural networks useful for modeling and control of accelerator processes?

- → ***Accelerators are intrinsically full of interesting dynamics:***
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  - → *Slow drift in machine characteristics due to instrument changes, minor (or not so minor) part replacements, device ageing, long-term process cycles*

- In addition, we have practical considerations which make adaptive control particularly appealing
  - High user demands on beam time → *need to run as continuously/seamlessly as possible*
  - Limited availability of time/funding fully dedicated to machine studies → *updates simultaneous to operation are desirable*

- In principle, the way forward for development/implementation of neural-network based control systems is relatively straightforward
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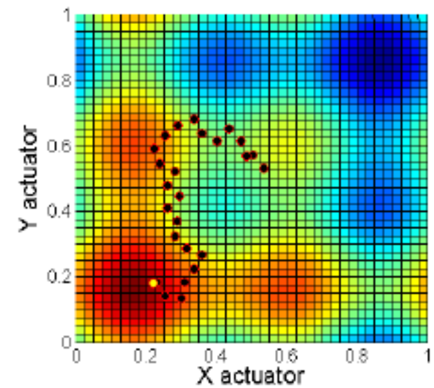
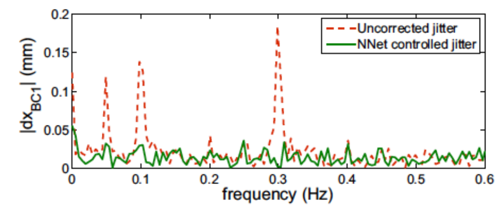
Existing Proof of Concept: Evelyne Meier's Ph.D. Thesis Work (co-advised by Dr. Biedron)

- Multi-objective optimization of beam parameters using reinforcement learning and a 2D objective function search space[1,2]
  - Example: implementation at Australian Synchrotron→ transmission from 90% to 97%, change in energy spread from 1.04% to 0.91%
- Neural network based feed-forward algorithms combined with PI feedback[3,4]
  - Example: implementation at LCLS → compensated for changes in energy and peak current resulting from induced jitter in the klystron phase and voltage
  - Showed the combined approach was more effective at correcting deliberately induced changes in parameters than either the feed-forward neural network or PI feedback approaches individually
- Immediate way forward from Evelyne's work (highly summarized) :
  - Further incorporation of adaptive components into combined feed-forward/ feedback systems
  - Optimization with search spaces greater than 2D



Example optimization search space
(Meier, Ph.D. thesis)



Example of neural network controller performance
(Meier, Ph.D. thesis)

1. E. Meier, S.G. Biedron, G. LeBlanc, M.J. Morgan, "Artificial Intelligence Systems for Electron Beam Parameters Optimisation at the Australian Synchrotron," Proceedings of IPAC'10, Kyoto, Japan.
2. E. Meier, S.G. Biedron, G. LeBlanc, M.J. Morgan, "Development of a novel optimization tool for electron linacs inspired by artificial intelligence techniques in video games," Nuclear Instruments and Methods in Physics Research Section A: Accelerators, Spectrometers, Detectors and Associated Equipment, Volume 632, Issue 1, 11 March 2011, Pages 1-6.
3. E. Meier, M. Morgan, S.G. Biedron, G. LeBlanc, J. Wu, "Development of a combined feed forward-feedback system for an electron Linac," Nucl. Instr. And Meth. A, Volume 609, Issues 2-3, 11 October 2009, Pages 79-88.
4. E. Meier, S.G. Biedron, G. LeBlanc, M.J. Morgan, and J. Wu, "Electron beam energy and bunch length feed forward control studies using an artificial neural network at the Linac coherent light source," Nucl.Instr. And Meth. A, Volume 610, Issue 3, 11 November 2009, Pages 629-635.

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→have already begun work (this week!) with RF gun cooling system

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- As a state-of-the-art test accelerator operating at the energy/intensity frontiers, ASTA will provide an environment which is particularly ripe with opportunity for development and testing of novel control schemes under demanding conditions

Basic Methodology for Supervised Training of a Neural Network

- Obtain enough data to construct both a training set and a validation set
- Determine which inputs are significant (i.e. have an influence above the noise)
  - Stepwise backward/forward regression of the model
- Train the network(s), i.e. use optimization techniques to minimize the cost function
- Optimize network topology (i.e. number of hidden nodes, layers)
- Use validation set to determine if the network is sufficiently generalizable within the parameter space in question

→ Goal is to find the simplest network which minimizes the mean squared error for the training set and for the validation set, while ensuring that these values are close to one another

Some Basic Training Classifications and Problem Types

- Supervised learning
  - Given data input and output, find an approximate mapping between the two sets
  - Used in static and dynamic modeling
- Reinforcement learning
  - Given an environmental input, generate an output/conduct an action, and observe the environmental response (with an associated cost)
  - Used for finding a minimal cost interaction strategy (optimization)
- Unsupervised learning
  - Given a set data, identify and assign classifications to underlying structures
  - Used in clustering, dimensional reduction (with preservation of similarities)