Machine Learning/AI for Accelerators: Activities at Fermilab and "vicinity"

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Issues to address

• Part I: Examples and Aspirations
  – At FNAL
  – two workshops
  – Snowmass

• Part II: Limits of AI/ML – “real complexities”
  – What is complexity
  – Hamlet → EO and Faust
  – Katsnelson and Kolmogorovs
  – Complexity of accelerators
Part I: AI/ML at Fermilab and “Around”
Two Workshops

AI/ML for Particle Accelerator, X-Ray Beamlines and Electron Microscopy

- **Description**: Ai for Particle Accelerators, X-ray Beamlines, and Electron Microscopy Workshop @ ANL.
  
  Advances in instrumentation have dramatically increased the complexities associated with experimental facilities. This includes enhanced facility capabilities as well as a substantial increase in the data generated. Consequently, the control and diagnostics of these experimental facilities are becoming increasingly complex, and the large output data streams necessitate smarter and more automated management and analyses of the data. Artificial Intelligence (AI) methods hold the promise of substantially improved management, control, and data analyses with the potential to dramatically increase experimental efficiencies as well as expanding and accelerating scientific discoveries.

  Argonne is the home to world-leading facilities such as the Advanced Photon Source (APS), the Argonne Tandem Linear Accelerator (ATLAS), the Argonne Wakefield Accelerator (AWA), and the Electron Microscopy Center at the Center for Nanoscale Materials (CNM). In order to highlight AI opportunities in these facilities, Argonne is hosting a workshop on AI for with participants drawn from 3 communities: particle accelerators, X-ray beamlines and electron microscopy. The goals of the workshop are:

AI for Accelerators - A Snapshot at Fermilab

- **Description**: Showcase of current work on AI/ML for accelerators. (no registration needed)

  What’s the buzz about Artificial Intelligence for our accelerator systems?

  Efforts have been ramping-up in the past couple of years to use Artificial Intelligence and Machine Learning (AI/ML) to enhance the performance of our accelerators and beamlines. We anticipate even more action in the coming year. Come hear from machine experts and engineers as they present advances in our latest AI/ML projects and what the future holds.

  **Audience take-aways:**
  1. What are the current AI/ML accelerator controls projects
  2. What are the plans for modernizing the accelerator control system to support AI/ML
  3. How do Accelerator Division's AI/ML endeavors support Fermilab

[https://indico.fnal.gov/event/50731/](https://indico.fnal.gov/event/50731/)

[https://indico.fnal.gov/event/52417/](https://indico.fnal.gov/event/52417/)
Examples of AI/ML Activities/Projects

1. Machine learning for Linac RF Optimization Longitudinal optimization
2. Booster Gradient Magnet Power Supply Control
3. “Big Data” Booster Control
4. Orbit Alignment at PIP2IT Using Bayesian Optimization
5. AI/ML for NuMI Target System Monitoring
6. Real-time quench detection
7. FAST/IOTA RF gun stabilization and optimization
8. MI loss minimization vs MI or RR situation
9. Stabilization of 8 GeV slow extraction from Muon-C ring
10. 6D Cooling optics design with ML elements
1. Machine learning for Linac RF Optimization

R. Sharankova, K. Seiya, M. Wesley, M. Mwaniki

- **Goal:** deliver stable, high intensity beam to users
  - Daily tuning of RF parameters to reduce beam loss and increase beam output

- **Challenges**
  - Tuning relies on robust and stable diagnostics data
  - Correlation of diagnostics data & RF parameters not always trivial
  - Cannot manually tune many RF parameters simultaneously

- **Approach**
  - Revisit/improve/add instrumentation
  - Explore ML techniques for RF regulation
    - Offline optimization of multiple RF parameters
    - Real-time momentum control

- **Success:**
  - Some visible… on the way to make operational
1. Fermilab Linac

- **Drift tube Linac**: 5 tanks
  - Resonant RF frequency 201 MHz
- **Side-coupled Linac**: 7 modules
  - Resonant RF frequency 805 MHz
- **Transition section**: Buncher & Vernier
  - Match beam structure b/n DTL & SCL

**Linac output**: 25 mA
**Pulse length**: 35 μsec
**Efficiency**: 94%

**Status**

- Linac output: 25 mA
- Pulse length: 35 μsec
- Efficiency: 94%
1. Real-time momentum control of a single cavity

- Beam loading causes energy spread along the Linac pulse
- Beam momentum going into Booster regulated by adjusting phase of SCL module 7
- Goal: reduce long-term momentum drift as well as momentum deviation in pulse
  - Real-time regulation based on ToF and other diagnostics
2. Offline optimization of multi-RF phases with ML

- Loss monitor, toroid and BPM patterns are correlated with RF parameters
- We aim to train a model to recognize those correlations, and find optimal RF setting for daily operations

3D pattern of total loss vs RFQ, Buncher and DTL tank 5 phase set points
• Booster injection efficiency is strongly dependent on the Booster RCS magnet current stabilization

• Proof-of-principle success:
  – machine learning models and demonstrated the feasibility of embedding such a model on a field-programmable gate array (FPGA) for a high-uptime, low-latency implementation
  – first developed a surrogate LSTM model, based on a recurrent neural network, to reproduce the behaviors of the real GMPS system in the context of the accelerator complex, establishing a safe environment for training reinforcement learning algorithms then trained a deep Q-network, based on a multilayer perceptron, to choose an optimal action (adjustment of one control knob) to maximize the long-term reward, taken from the negative absolute value of the regulation error (difference between the set and observed values of the minimum GMPS current)
  – found this surrogate-trained network achieved a factor of 2 improvement over the existing controller in terms of the achieved rewards (goal was x10).

• Operational implementation ongoing
2. Booster GMPS – 15 Hz cycle

**GMPS AI: The Need for Improving Regulation**

- **Observed \( \delta I / I \)** for min and max currents: \( \sim 10^{-3} \) each

- **Perturbing influences:**
  - Recent corrections made
  - Other nearby synchrotrons
  - Fluctuation of 60 Hz power
  - Temperatures, etc

- **Available data mostly with the current PID regulator**

- **Spread in B-field degrades beam quality, degrades repeatability, & contributes to losses**
2. Booster GMPS – Existing PID Circuit Regulation

Reference system: B coil, transducer, dB/dt coil, zero-crossing

Accelerator Control Network

- Human experts adjust target settings from time to time via control system
- Also records settings & readings with some unknown latency

GMPS control rack

Programmable logic

- Known factors excluded from PID control logic: Line Voltage variation, Gallery temperatures, etc.

Power supplies 1-4

control signals

sampled \( I_{\text{min}}, I_{\text{max}} \)

series connect
2. Booster GMPS – AI Improves Stabilization \( \sim x2 \)

**GMPS AI**: Digital Twin as RL Environment

With LSTM providing environment, trained an MLP agent to tweak **B:VIMIN** prescription each timestep

- Reward function: neg. abs. error = \(-|B:IMINER|\)
- Q-learning @ 50 timestep episodes
  - Double DQN (target & policy model distinct)
  - 32-experience (random) to update policy model
  - \( \epsilon \)-greedy decay factor 0.9995 (min: 0.0025)
  - Discretized options to change **B:VIMIN**:
    - 0 (no change), \( \pm 0.0001, \pm 0.005, \) and \( \pm 0.001 \).
  - 3 layers of 56 ReLU nodes
3. “Big Data” Booster Control System

Bill Pellico

• Problem:
  – “Data loggers” stores ~2500 channels of Booster control
  – Operators use only some… trained on repeating problems
  – Understanding reasons for any changes is challenging and time consuming

• Goal:
  – Find a way for faster optimization/return to stable operation

• Approach
  – Train AI/ML circuits to analyse “data logger” data

• Status:
  – Just started.. Asked DOE for $$
4. Orbit Alignment at PIP2IT Using Bayesian Optimization

Pavlo Lyalyutskyy, Eduard Pozdeyev

- Beam orbit alignment in PIP2IT using Bayesian Optimization with Gaussian Processes
- PIP-II Injector Test (PIP2IT) facility is near-complete Front End of PIP-II accelerator with two first cryomodules
- Beam trajectory is perturbed by misaligned cavities and magnets
  - Measured by Beam Position Monitors (BPMs)
  - Orbit is steered by orbit corrector magnets
- Task: reduce orbit deviation in BPMs
4. PIP2IT Bayesian Optimization with Gaussian Processes

1. Choose a surrogate model and define a prior.

\[ f(x_{1:k}) \sim \text{Normal}\left(\mu_0(x_{1:k}), \Sigma_0(x_{1:k}, x_{1:k})\right) \]

2. Use Bayes Rule to update our prior to get the posterior.

\[ f(x|f(x_{1:n})) \sim \text{Normal}(\mu_n(x), \sigma_n^2(x)) \]

\[
\mu_n(x) = \Sigma_0(x, x_{1:n})\Sigma_0(x_{1:n}, x_{1:n})^{-1}(f(x_{1:n}) - \mu_0(x_{1:n})) + \mu_0(x)
\]

\[
\sigma_n^2(x) = \Sigma_0(x, x) - \Sigma_0(x, x_{1:n})\Sigma_0(x_{1:n}, x_{1:n})^{-1}\Sigma_0(x_{1:n}, x).
\]

3. Use an acquisition function \( \alpha(x) \) to decide next point to sample.

\[ x_t = \arg\max_{x \in A} \alpha(x) \]

4. Add newly sampled point to the observations and go to step #2, until convergence.
4. PIP2IT Success – x2-3 faster convergence than Simplex

Convergence with 26 free parameters (degrees of freedom). Convergence in ~30 steps. Convergence several times faster than Simplex.
5. AI/ML for NuMI Target System Monitoring

Athula Wickremasinghe, Katsuya Yonehara

Challenge:

NuMI target system is the world's brightest neutrino beam source for neutrino oscillation experiments. The goal of target system AI is predicting a beam related systematic uncertainty for a neutrino flux per beam spill.

Context:

- **The Validation of target system AI (present work)**
  - There are three layers of muon monitors and each monitor provides 9 x 9 pixel image. Our first AI analyzes the image to predict beam position at the target, horn current, and beam intensity per beam spill.

- **Anomaly detection (future work)**
  - Collect muon monitor and other instrumentation signals to catch any accidental changes of beam element (target density deterioration, misalignments of elements, water condensation in the beam line, etc).

- **Prediction of neutrino flux (future work)**
  - Train AI with Monte Carlo simulations to predict a neutrino flux at neutrino detectors by using the observed muon monitor signals.
5. AI/ML for NuMI Target Results

- The contour plot is mapping out the regions based on the high to low values of the standard errors on predictions.

- The tuned model has a good capability of predicting the beam position horizontal and vertical, beam intensity and horn current with the standard error of +/- 0.018 mm, +/-0.013mm, +/- 0.05 E12 and +/- 0.10 kA respectively. Those are well below the required accuracy of beam related systematic uncertainty.

- Planning to implement the ML model predictions for daily NuMI beamline data monitoring.

- NuMI beam simulation studies are ongoing to predict neutrino flux.
6. Real-time quench detection

Superconducting Magnet Quenches

- In order to maintain superconductivity, superconducting magnets typically operate at or below liquid helium temperature.

- Due to several reasons (mechanical imperfections, conductor motions, ...), a specific spot in the magnet may heat up.

- This can eventually cause the whole magnet to become resistive. And with huge amount of current pumping through, it can be catastrophic.

Magnet "training" requires 10s of quench events

Duc Hoang, Christian Boffo, et al
6. Real-time quench detection

Challenges:
Physics of quenches are not well-understood
- Typically are detected (milli-)seconds after the event happens
- Magnet training is expensive (~$300k, 2 weeks per magnet)
  - future colliders and high TC superconductors even more important
- Can we understand and potentially mitigate quench events?
- Use (acoustic and other) sensors to detect precursors to the quench
6. Anomaly detection with continuous learning

"Simple" ML algos using statistical features of time series data

- Training model
- Data pre-processing
- Update model’s state
- Evaluation of reconstruction loss
- Greater than threshold? trigger

Step size: 100 μs
Window size: 20 ms
Time label associated with the window.

MQXFS1d (5 sensors)
- 12 inputs
- Encoder: 6 nodes activation: ELU
- (Latent space) 3 nodes activation: ELU
- Decoder 6 nodes activation: ELU
- Reconstructed Output 12 outputs

MDPCT1b (2 sensors)
- 6 inputs
- Encoder: 4 nodes activation: ELU
- (Latent space) 2 nodes activation: ELU
- Decoder 4 nodes activation: ELU
- Reconstructed Output 6 outputs
6. **Success:** Detected 77% of anomalous events ahead of the quench (<15s)

A lot more interesting data analysis that can be done and would like to build a real-time platform!
7. FAST/IOTA RF gun stabilization and optimization

Auralee started at FAST…

.. then Argonne and SLAC

.. Now Jinhao Ruan trying to make the ML system operational at FAST Run 4
Overview of IOTA & FAST linac

- 1.3 GHz photocathode RF gun
  - PITZ style gun with solenoid and bucking coil
  - Beam accelerated to ~4 MeV
- 1.3 GHz 9-cell Tesla type cavities
  - Beam accelerated to ~35 MeV
ML to stabilize FAST 1.3 GHz (Copper) RF gun

Basic concept:
1. Use a predictive model to assess the outcome of possible future actions
2. Choose the best series of actions
3. Execute the first action
4. Gather next time step of data
5. Repeat
Improvement: x5 faster stabilization or RF gun

A 1-°C step change under the existing feed-forward/PI controller. Note that the oscillations are due to the time delays, thermal responses, and recurrent effect of the water system, not a poorly tuned set of PI gains.

(same scale plot) A 1-°C step change in TCAV under the benchmark MPC. Note that the scales are smaller than those of Fig. 2. These data were recorded as part of a series of steps in the TCAV set point. Note that this is not a perfect 1-°C step, as there is an offset between the original TCAV set point and the final value it obtained in the prior to step.
Current developments (J.&A.Edelen, D.Edstrom)

• Expand the AI/ML experience onto FAST emittance optimization

Goal: Full phase-space control at the entrance of the cryomodule using virtual cathode images, magnet settings, cavity phases, and cavity amplitudes
NN Architecture: 1\textsuperscript{st} trained on Simulations

- Data separated into Training, Validation, and Test sets
  - Training set: used directly in training
  - Validation set: interleaved with training data but not used explicitly in training
  - Test set: outside range of training data
- Noise added to the data before training
- Performance across validation and test set
  - Top: prediction and simulation as a function of gun phase
  - Bottom: rms percent error between neural network and simulations
- All output parameters perform well except transmission
  - All transmission is 100\% in our range of simulations so this is dominated by noise added during training
NN: Then trained on measurements

- **Updating with measurements**
  - Top Left: Normalized emittance as a function of sample number for updated dataset
  - Top Right: Alpha as a function of sample number for updated dataset
- **Network retains the information from the simulations**
  - Right: comparison of network prediction for phase scan data from before and after updating with measurements
Auralee’s Comments (2022 Workshop)

Bayesian Optimization

Select sample $x \rightarrow$ observe objective $\rightarrow$ refit surrogate model $\rightarrow$ use model predictions and uncertainty to choose next point according to an acquisition function.

Analogous concepts, different terminology and usually different setting:

- objective $\rightarrow$ reward
- surrogate model $\rightarrow$ value function
- acquisition function $\rightarrow$ policy
- acquire new sample $\rightarrow$ take an action

Reinforcement Learning

Many ways to construct agent that learns from reward:

- $\text{Agent} \rightarrow \text{actions} \rightarrow \text{System} \rightarrow \text{Reward} = \sum r$

Observe state $\rightarrow$ take action according to a control policy $\rightarrow$ observe reward $\rightarrow$ update policy or value function.
8-10. (very briefly)

8. MI loss minimization vs MI or RR situation
   • Losses at extraction from MI (120 GeV) depend on Main Injector RCS and on injector (8 GeV RecyclerRing)
   • ML algorithm allow to decouple causes MI vs RR

9. Stabilization of 8 GeV slow extraction from Muon-C ring
   • Efficiency and stability slow extr (2nd order) proton current from Muon-Campus ring depends on may parameters
   • AI/ML to help to stabilize

10. 6D Cooling optics design with ML elements
    • Muon Collider needs ~50 6-D ionization cooling cells, final emittance strongly dependent on ~200 parameters
    • AI/ML help to get optimum and predict the best way to tune the system in the future
Part II:
On Truly Complex Systems
(which AI & ML are not yet capable of, but might be some day…)

03/23/22 Shiltsev | ML/AI @BSW22
What is complexity?

• Something that we immediately recognize when we see it, but very hard to define quantitatively

• S. Lloyd, “Measures of complexity: a non-exhaustive list” – 40 different definitions

• Can be roughly divided into two categories:
  - computational/descriptive complexities
  - effective/physical or structural complexities
Computational and descriptive complexities

• Prototype – the *Kolmogorov complexity:* the length of the shortest description (in a given language) of the object of interest

• Examples:
  - Number of gates (in a predetermined basis) needed to create a given state from a reference one
  - Length of an instruction required by file compressing program to restore image
Future Collider Proposals: 8 Higgs/EW factories

<table>
<thead>
<tr>
<th>Name</th>
<th>Details</th>
</tr>
</thead>
<tbody>
<tr>
<td>CepC</td>
<td>$e^+e^-, \sqrt{s} = 0.24$ TeV, $L = 3.0 \times 10^{34}$</td>
</tr>
<tr>
<td>CLIC (Higgs factory)</td>
<td>$e^+e^-, \sqrt{s} = 0.38$ TeV, $L = 1.5 \times 10^{34}$</td>
</tr>
<tr>
<td>ERL ee collider</td>
<td>$e^+e^-, \sqrt{s} = 0.24$ TeV, $L = 73 \times 10^{34}$</td>
</tr>
<tr>
<td>FCC-ee</td>
<td>$e^+e^-, \sqrt{s} = 0.24$ TeV, $L = 17 \times 10^{34}$</td>
</tr>
<tr>
<td>gamma gamma</td>
<td>X-ray FEL-based $\gamma\gamma$ collider</td>
</tr>
<tr>
<td>ILC (Higgs factory)</td>
<td>$e^+e^-, \sqrt{s} = 0.25$ TeV, $L = 1.4 \times 10^{34}$</td>
</tr>
<tr>
<td>LHeC</td>
<td>$ep, \sqrt{s} = 1.3$ TeV, $L = 0.1 \times 10^{34}$</td>
</tr>
<tr>
<td>MC (Higgs factory)</td>
<td>$\mu\mu, \sqrt{s} = 0.13$ TeV, $L = 0.01 \times 10^{34}$</td>
</tr>
</tbody>
</table>

CLIC NCRF 72 MV/m
11 km

CepC/FCCee
100 km
100MW RF

ILC SRF 31.5 MV/m
21 km
## 17 (!) High Energy Collider Concepts/Proposals

<table>
<thead>
<tr>
<th>Name</th>
<th>Details</th>
</tr>
</thead>
<tbody>
<tr>
<td>Cryo-Cooled Copper linac</td>
<td>$e^+e^-, \sqrt{s} = 2 \text{ TeV}, L = 4.6 \times 10^{34}$</td>
</tr>
<tr>
<td>High Energy CLIC</td>
<td>$e^+e^-, \sqrt{s} = 1.5 - 3 \text{ TeV}, L = 5.9 \times 10^{34}$</td>
</tr>
<tr>
<td>High Energy ILC</td>
<td>$e^+e^-, \sqrt{s} = 1 - 3 \text{ TeV}$</td>
</tr>
<tr>
<td>FCC-hh</td>
<td>$pp, \sqrt{s} = 100 \text{ TeV}, L = 30 \times 10^{34}$</td>
</tr>
<tr>
<td>SPPC</td>
<td>$pp, \sqrt{s} = 75/150 \text{ TeV}, L = 10 \times 10^{34}$</td>
</tr>
<tr>
<td>Collider-in-Sea</td>
<td>$pp, \sqrt{s} = 500 \text{ TeV}, L = 50 \times 10^{34}$</td>
</tr>
<tr>
<td>LHeC</td>
<td>$ep, \sqrt{s} = 1.3 \text{ TeV}, L = 1 \times 10^{34}$</td>
</tr>
<tr>
<td>FCC-eh</td>
<td>$ep, \sqrt{s} = 3.5 \text{ TeV}, L = 1 \times 10^{34}$</td>
</tr>
<tr>
<td>CEPC-SPPpC-eh</td>
<td>$ep, \sqrt{s} = 6 \text{ TeV}, L = 4.5 \times 10^{33}$</td>
</tr>
<tr>
<td>VHE-ep</td>
<td>$ep, \sqrt{s} = 9 \text{ TeV}$</td>
</tr>
<tr>
<td>MC – Proton Driver 1</td>
<td>$\mu\mu, \sqrt{s} = 1.5 \text{ TeV}, L = 1 \times 10^{34}$</td>
</tr>
<tr>
<td>MC – Proton Driver 2</td>
<td>$\mu\mu, \sqrt{s} = 3 \text{ TeV}, L = 2 \times 10^{34}$</td>
</tr>
<tr>
<td>MC – Proton Driver 3</td>
<td>$\mu\mu, \sqrt{s} = 10 - 14 \text{ TeV}, L = 20 \times 10^{34}$</td>
</tr>
<tr>
<td>MC – Positron Driver</td>
<td>$\mu\mu, \sqrt{s} = 10 - 14 \text{ TeV}, L = 20 \times 10^{34}$</td>
</tr>
<tr>
<td>LWFA-LC (e+e- and $\gamma\gamma$)</td>
<td>Laser driven; $e^+e^-, \sqrt{s} = 1 - 30 \text{ TeV}$</td>
</tr>
<tr>
<td>PWFA-LC (e+e- and $\gamma\gamma$)</td>
<td>Beam driven; $e^+e^-, \sqrt{s} = 1 - 30 \text{ TeV}$</td>
</tr>
<tr>
<td>SWFA-LC</td>
<td>Structure wakefields; $e^+e^-, \sqrt{s} = 1 - 30 \text{ TeV}$</td>
</tr>
</tbody>
</table>
Accelerator Complexity

- Complexity to design (many dissimilar systems)
- Complexity to build (# elements, # of systems, level of each system – “standard/off-shelf, special, unique”)
- Complexity to reach energy = “make it work” (reliability)
- Complexity to reach performance “lumi” – CPT theorem:

\[ C \cdot P = T \]
\[ L(t_0 + T) = L(t_0) \times e^{T/C} \]

Table 1. “Complexities” of colliding beam facilities.

<table>
<thead>
<tr>
<th>Facility</th>
<th>C, years</th>
<th>Interval</th>
</tr>
</thead>
<tbody>
<tr>
<td>SLC (e^+e^-)</td>
<td>1.6 ± 0.1</td>
<td>1989–1997</td>
</tr>
<tr>
<td>Tevatron Run II (p-\bar{p})</td>
<td>2.0 ± 0.2</td>
<td>2002–2007</td>
</tr>
<tr>
<td>RHIC (p-\bar{p})</td>
<td>2.2 ± 0.3</td>
<td>2000–2004</td>
</tr>
<tr>
<td>HERA (p-\bar{p})</td>
<td>2.8 ± 0.4</td>
<td>1992–2005</td>
</tr>
<tr>
<td>SppS (p-\bar{p})</td>
<td>3.3 ± 0.2</td>
<td>1982–1990</td>
</tr>
<tr>
<td>LEP (e^+e^-)</td>
<td>3.3 ± 0.3</td>
<td>1989–1995</td>
</tr>
<tr>
<td>ISR (p-\bar{p})</td>
<td>3.7 ± 0.3</td>
<td>1972–1982</td>
</tr>
<tr>
<td>CESR (e^+e^-)</td>
<td>4.4 ± 0.4</td>
<td>1984–1997</td>
</tr>
</tbody>
</table>

LHC Lx100 in 2010-2018 (8 yrs) \(\rightarrow\) Complexity=8/4.6=1.74
On Complexity as Measure of Difficulty to Reach Performance (#4)
### Table 3. Tevatron Collider Run II major luminosity improvements history.

<table>
<thead>
<tr>
<th>Improvement</th>
<th>Luminosity gain</th>
</tr>
</thead>
<tbody>
<tr>
<td>Optics correction in Accumulator (AA) to Main Injector (MI) beam line</td>
<td>12/2001</td>
</tr>
<tr>
<td>Tevatron quenches on abort stopped by electron lens</td>
<td>02/2002</td>
</tr>
<tr>
<td>Antiproton loss at the step #13 of Tevatron low-beta squeeze fixed</td>
<td>04/2002</td>
</tr>
<tr>
<td>New Tevatron injection helix implemented</td>
<td>05/2003</td>
</tr>
<tr>
<td>New AA lattice reduces IBS, emittances</td>
<td>07/2003</td>
</tr>
<tr>
<td>Beam Line Tuner to reduce emittance dilution at Tevatron injection</td>
<td></td>
</tr>
<tr>
<td>Antiproton multi-bunch coalescing efficiency improved in MI</td>
<td></td>
</tr>
<tr>
<td>Small aperture Lambertson magnets removed from Tevatron C0 sector</td>
<td></td>
</tr>
<tr>
<td>Tevatron sextupoles tuned / SEMs taken out of antiproton beam line</td>
<td>07/2003</td>
</tr>
<tr>
<td>New Tevatron helix implemented on ramp to reduce beam loss</td>
<td>07/2003</td>
</tr>
<tr>
<td>Tevatron magnet reshimming (to center coils inside iron yoke)</td>
<td>07/2003</td>
</tr>
<tr>
<td>MI damps operations / HEP store length increased</td>
<td>02/2004</td>
</tr>
<tr>
<td>Improved efficiency of 2.5 MHz antiproton transfer</td>
<td>04/2004</td>
</tr>
<tr>
<td>Reduction of Tevatron β* to 35 cm</td>
<td>05/2004</td>
</tr>
<tr>
<td>Antiproton injections from both Recycler and secondary ring</td>
<td>07/2004</td>
</tr>
<tr>
<td>Electron cooling system in Recycler operating as a functioning device</td>
<td>01–07/2005</td>
</tr>
<tr>
<td>Longitudinal slip-stacking system in MI to improve the luminosity</td>
<td>03/2005</td>
</tr>
<tr>
<td>Tevatron octupoles optimized at injection energy to 15 GeV</td>
<td>04/2005</td>
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<tr>
<td>Further reduction of the Tevatron β* to 28 cm</td>
<td>09/2005</td>
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<tr>
<td>Antiproton production optimized</td>
<td>02/2006</td>
</tr>
<tr>
<td>Tevatron helical separation at 183 GeV improved, more protons</td>
<td>06/2006</td>
</tr>
<tr>
<td>Tevatron collision helix improved, better lifetime</td>
<td>07/2006</td>
</tr>
<tr>
<td>New Recycler working with smaller antiproton emittances</td>
<td>07/2006</td>
</tr>
<tr>
<td>Faster antiprotons from AA to RR (1 hour → 1 min)</td>
<td>12/2006</td>
</tr>
<tr>
<td>New antiproton beam gradient Li lens operational</td>
<td>01/2007</td>
</tr>
<tr>
<td>Tevatron sextupoles exhaust set up for new working point</td>
<td>07/2007</td>
</tr>
<tr>
<td>Complementary high chromaticity in Tevatron beam optics</td>
<td>08/2007</td>
</tr>
<tr>
<td>Shutdowns in fixed by multi-bunch proton injection</td>
<td>08/2008</td>
</tr>
<tr>
<td>Better quality of collimator due to scraping in Main Injector</td>
<td>09/2008</td>
</tr>
<tr>
<td>Antiproton size dilution at collisions / B0 aperture opened up</td>
<td>04/2009</td>
</tr>
<tr>
<td>Booster proton emittances reduced / tune up of P1 and A1 transfer lines</td>
<td>04/2009</td>
</tr>
<tr>
<td>Tevatron collimators employed during low-beta squeeze, more protons</td>
<td>04/2010</td>
</tr>
</tbody>
</table>

*Note: The improvement x43 in luminosity in 32 steps was highlighted.*
CPT Theorem for Accelerators

\[ C \times P = T \]

- **C** = Complexity of the machine
- **P** = Performance (or Challenge)
- **T** = Time to reach \( P \)

\[ P = \ln(\text{Lumi Increase Ratio}) \]

\[ T = \text{Time to reach } P \]

\[ i.e., L(T) = L(0) \times \exp\left(\frac{T}{C}\right) \]
Tevatron Luminosity Progress

![Graph showing Tevatron Peak Luminosity over time with markers at 2001, 2004, 2007, and 2010 with values C=0.7, C=2.0, and C=8.6.]
Complexity of Beams in log-Scale (TV tube=0)

- **Complexity 0.5**: light sources
  - $e^-$

- **Complexity 1**: p-synchrotron
  - $p$

- **Complexity 1**: B-factories
  - $e^-$, $e^+$

- **Complexity 1.5**: eCool, HERA, EIC
  - $p$

- **Complexity 2**: DCI-Orsay, ’80
  - $e^+$, $e^-$

- **Complexity 2**: Tevatron, LHC
  - $p$, $p^\bar{}$, $p^\bar{}$

- **Complexity 2.5**: Tev+elens BBC
  - $e^-$, $p$, $p^\bar{}$
LHC Luminosity Outlook: 2003 Vision

- Radiation damage limit: ~700 fb⁻¹
- Time to halve error: [years]
- Integrated $L$: [100 fb⁻¹]
- $L$ at end of year
- Design luminosity
- Ultimate luminosity

[Graph showing luminosity outlook from 2007 to 2017]

Courtesy: J. Strait
LHC Luminosity CPT-Prediction (2006)

![Graph showing LHC luminosity predictions from 2008 to 2016 with different scenarios and LHC design luminosity between 2014-2017.]
LHC: Design Lumi in July 2016

Achieved 6 years since 1st collisions in April’2010
Structural Complexity: Hierarchy and Patterns

Multi-scale structural complexity of natural patterns

Andrey A. Bagrov, Ilia A. Iakovlev, Mikhail I. Katsnelson, and Vladimir V. Mazurenko

The idea (from holographic complexity and common sense):
Complexity is dissimilarity at various scales

Let \( f(x) \) be a multidimensional pattern

\[ f_\Lambda(x) \] its coarse-grained version (Kadanoff decimation, convolution with Gaussian window functions, ...)

Complexity is related to distances between \( f_\Lambda(x) \) and \( f_{\Lambda+d\Lambda}(x) \)

\[
\Delta_\Lambda = |\langle f_\Lambda(x) | f_{\Lambda+d\Lambda}(x) \rangle - \frac{1}{2} (\langle f_\Lambda(x) | f_\Lambda(x) \rangle + \langle f_{\Lambda+d\Lambda}(x) | f_{\Lambda+d\Lambda}(x) \rangle) | = \frac{1}{2} |\langle f_{\Lambda+d\Lambda}(x) - f_\Lambda(x) | f_{\Lambda+d\Lambda}(x) - f_\Lambda(x) \rangle |,
\]

\[
c = \sum_{\Lambda} \frac{1}{d\Lambda} \Delta_\Lambda \to \int |\frac{\partial f}{\partial \Lambda} | d\Lambda, \text{ as } d\Lambda \to 0
\]
Main Message

• Complexity is about
  – **Dissimilarity**
    • Magnets, RF, plasma, cooling, drivers, FF, etc
  – **And Hierarchy:**
    • Eg LHC 1 ring
      O(10) sectors
      O(100) cells
      O(1000) main magnets
      O(10^4) aux magnets,
      O(10^5) control channels

• Other “Pyramids” (RF linacs/cavities, injectors, etc)
More on Hierarchy and Complexity

• Complexity is \( \sim \log(\text{# elements}) \):
  • Eg if complexity of 1 element is 1
  • complexity of 10 elements is 2
  • complexity of 100 elements is 3
  • complexity of 1000 elements is 4
  • complexity of \(10^4\) elements is 5
  • complexity of \(10^5\) elements is 6

• Unfamiliarity is another factor
  – Advanced vs Traditional - add a unit (ie 10 SC 8 T \(\sim\) 100 NC) or more
  – Beyond state-of-art vs advanced – add a unit (16T \(\sim\)10x 8 T) or more

• Complexity of accelerators change in time
  – As technology progresses and experience accumulated
  – i.e. building the LHC looked much harder 20 years ago than now…
# Table of Complexities (just an attempt)

<table>
<thead>
<tr>
<th></th>
<th>$\Delta C$ of Magnets</th>
<th>$\Delta C$ of RF cav</th>
<th>$\Delta C$ of Injectors</th>
<th>$\Delta C$ of cool/prod</th>
<th>$\Delta C$ of FF</th>
<th>$C$ Sum</th>
</tr>
</thead>
<tbody>
<tr>
<td>LHC</td>
<td>4.5</td>
<td>1</td>
<td>2.5</td>
<td></td>
<td></td>
<td>8</td>
</tr>
<tr>
<td>Tevatron</td>
<td>4</td>
<td>1</td>
<td>2.5</td>
<td>2</td>
<td></td>
<td>9.5</td>
</tr>
<tr>
<td>XFEL</td>
<td>1</td>
<td>4</td>
<td>1</td>
<td></td>
<td></td>
<td>6</td>
</tr>
<tr>
<td>ILC-0.25</td>
<td>1</td>
<td>5</td>
<td>2</td>
<td>1 (e+)</td>
<td>1</td>
<td>10</td>
</tr>
<tr>
<td>ILC-3</td>
<td>2</td>
<td>6</td>
<td>2</td>
<td>1 (e+)</td>
<td>1.5</td>
<td>12.5</td>
</tr>
<tr>
<td>CLIC-0.38</td>
<td>2</td>
<td>5</td>
<td>2</td>
<td>1.5 (drive)</td>
<td>1</td>
<td>11</td>
</tr>
<tr>
<td>CLIC-3</td>
<td>3</td>
<td>6</td>
<td>2</td>
<td>2 (drive)</td>
<td>1.5</td>
<td>14.5</td>
</tr>
<tr>
<td>C^3-0.25</td>
<td>1.5</td>
<td>4.5</td>
<td>2</td>
<td>1 (e+)</td>
<td>1</td>
<td>10</td>
</tr>
<tr>
<td>FCCee</td>
<td>4</td>
<td>3</td>
<td>3-3.5</td>
<td></td>
<td></td>
<td>10-10.5</td>
</tr>
<tr>
<td>MC-3</td>
<td>2.5-3</td>
<td>3</td>
<td>2.5-3</td>
<td>2.5</td>
<td></td>
<td>10-11</td>
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<tr>
<td>MC-10</td>
<td>3-3.5</td>
<td>3-3.5</td>
<td>3</td>
<td>2.5</td>
<td></td>
<td>11.5-12.5</td>
</tr>
<tr>
<td>FCChh</td>
<td>5-6</td>
<td>2</td>
<td>4</td>
<td></td>
<td></td>
<td>11-12</td>
</tr>
<tr>
<td>L/PWA-1</td>
<td>3</td>
<td>4-5</td>
<td>2</td>
<td>2 (drive)</td>
<td>1.5</td>
<td>13.5-14.5</td>
</tr>
</tbody>
</table>

+1 unit of complexity $\sim e^{0.5-1}$ times harder?