Machine Learning for Online Applications and Control

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GARD ABP Workshop 2: Working Group #1
(advanced accelerator instrumentation and controls)

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U.S. DEPARTMENT OF ENERGY
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Grand Challenges and How We're Addressing Them

- Grand challenge #1 (beam intensity):
  - *Better online models and tuning algorithms will enable accelerators to operate closer to the ideal configurations*

- Grand challenge #2 (beam quality):
  - *Improved controls will help operational machines realize theoretical limits on beam quality*

- Grand challenge #3 (beam control):
  - *Better online models and tools integrated with accelerator operations directly address the need for better beam control*

- Grand Challenge #4 (beam prediction):
  - *Online modeling using as-built simulations augmented with measured data from the machine is a powerful tool for beam-prediction*

How do better online tools impact the DOE mission?

- The primary scientific mission of the ABP thrust is to address and resolve the Accelerator and Beam Physics Grand Challenges. Other equally important ABP missions are associated with the overall DOE HEP missions:
  - *Advance physics of accelerators and beams to enable future accelerators*
    - Uniform tools enable easier collaboration and allow scientists and engineers to more quickly solve challenging control problems
  - *Develop conventional and advanced accelerator concepts and tools to disrupt existing costly technology paradigms in coordination with other GARD thrusts*
    - The next generation of accelerators requires advanced controls to meet their performance metrics
  - *Guide and help to fully exploit science at the GARD beam facilities and operational accelerators*
    - Improved controls at facilities maximize beam time for users and enable more cutting edge physics
  - *Educate and train future accelerator physicists*
    - A library of working ML examples lowers the barrier to entry for scientists solving problems in accelerators

Machine agnostic tools will help the community advance together

- Some online modeling, analysis, and tuning programs in use or under development
  - *MATLAB Middle Layer / Accelerator Toolbox (Spear3 + NSLS-II + Others)*
  - *OCELOT (DESY + SLAC + Others)*
  - *GPU Accelerated PARMILA (LANL)*
  - *RHIC Lattice Translator (BNL + Plans for EIC)*
  - *LUME, Simulacrum (SLAC)*
  - *PyEpics (in use at APS / JLab / SLAC)*
  - *LCLSTools (SLAC)*

- A proposed path forward: bridge gaps between accelerator facilities by integrating tools into an intuitive interface with a library of worked examples
  - *Browser-based GUIs lower the barrier to entry and enable more seamless collaboration*
  - *Library of successful examples will allow users to quickly build robust custom solutions*
  - *RadiaSoft plans to test and deploy such tools at BNL, JLab and Fermilab*

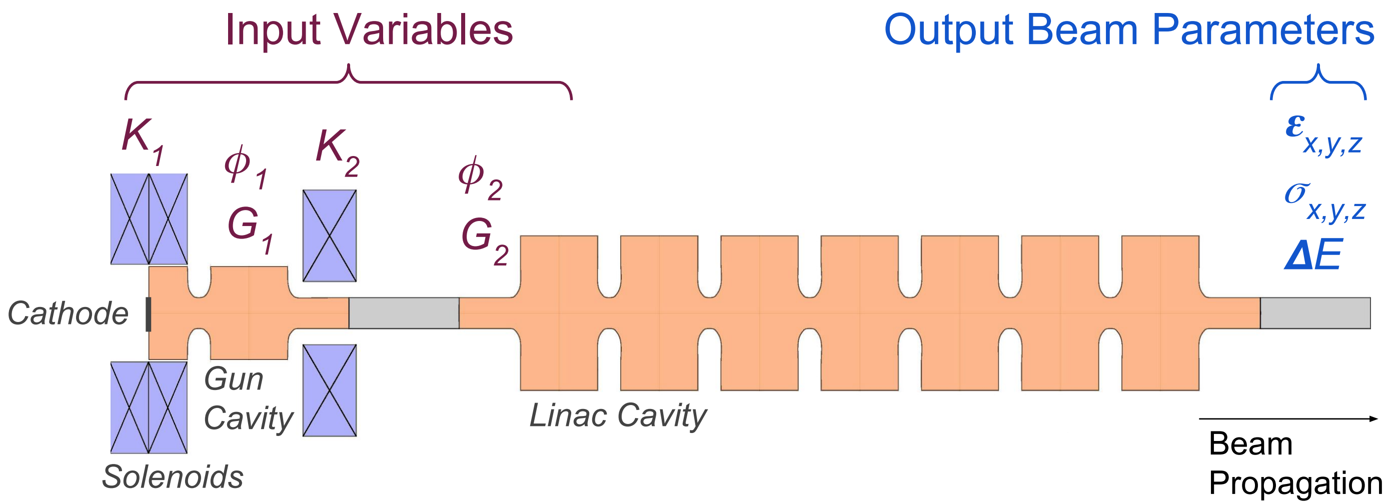
Surrogate modeling enables rapid optimization of high brightness photo injector

Test Case: Argonne Wakefield Accelerator Injector

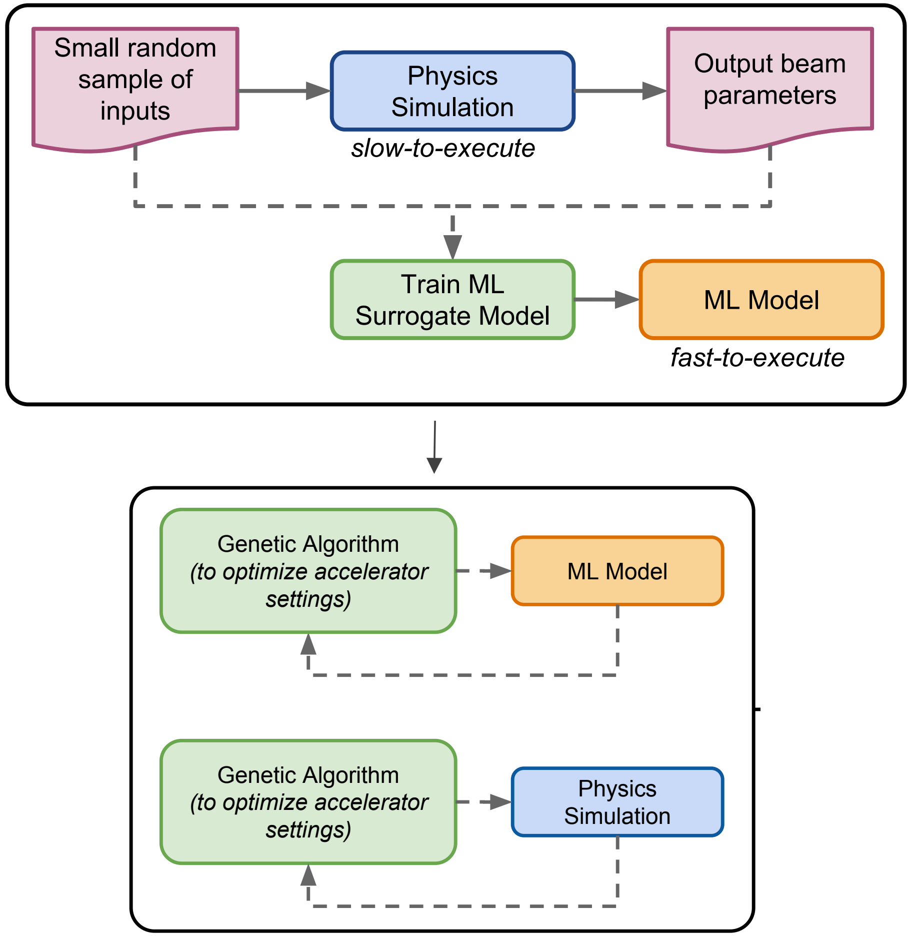
OPAL simulation (PIC) :
3D space charge
3D field maps

NSGA-II for optimization:
200 generations
~350 individuals

100 - 5K random points for training



Generate ML Model using Sparse Random Sample



A. Edelen, et al., PRAB 23, 044601 (2020)

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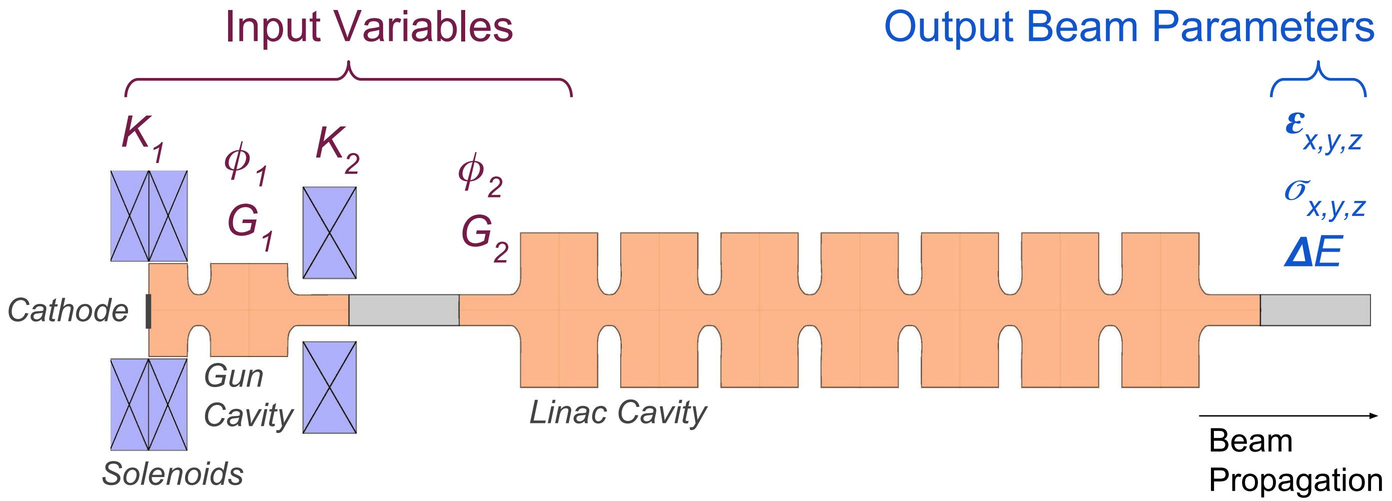

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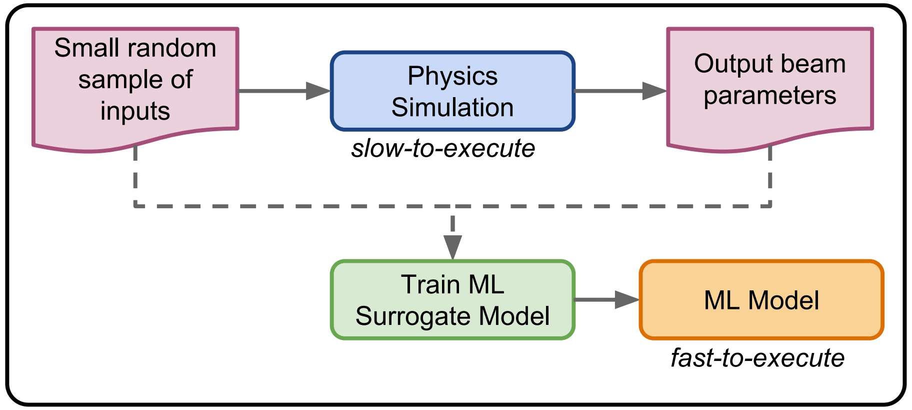
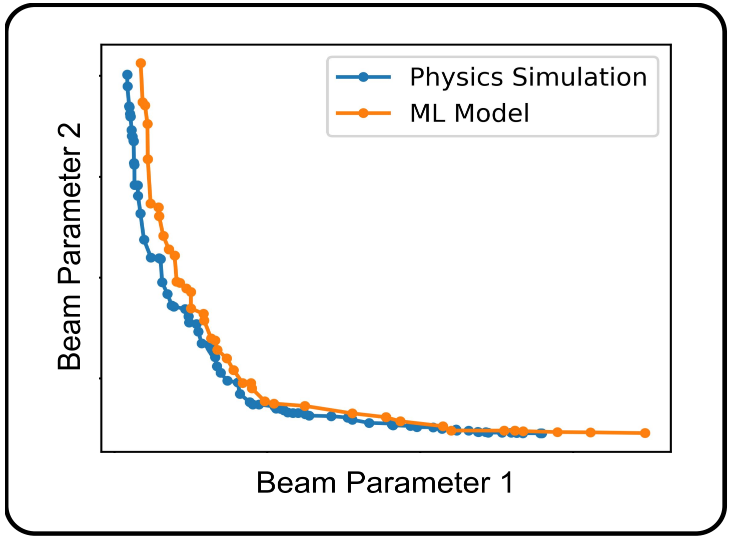


Compare Resulting Pareto Fronts



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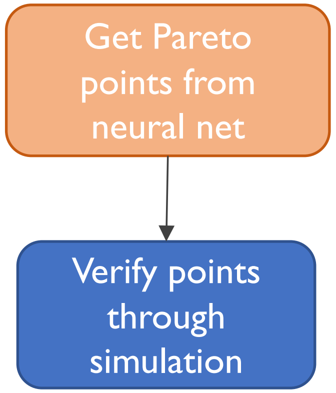
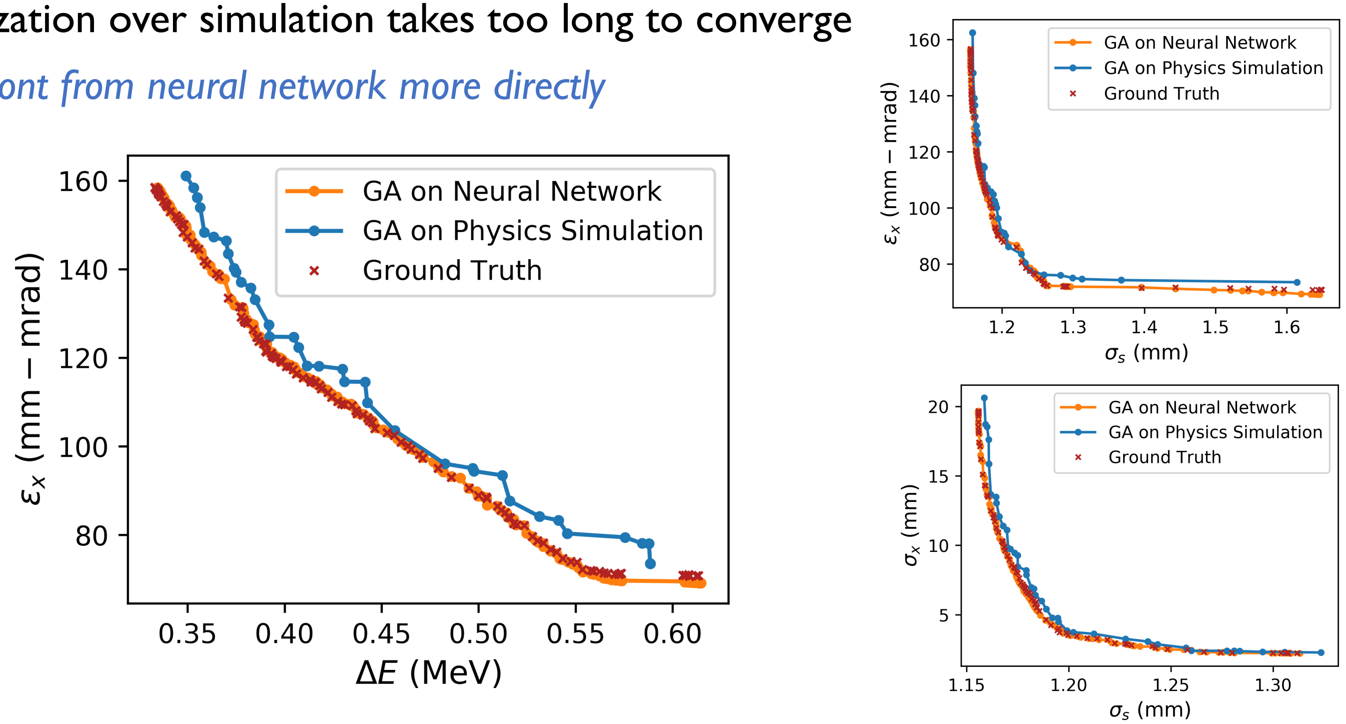
Verifying Pareto front from the neural network

In some cases, optimization over simulation takes too long to converge

→ *validate Pareto front from neural network more directly*

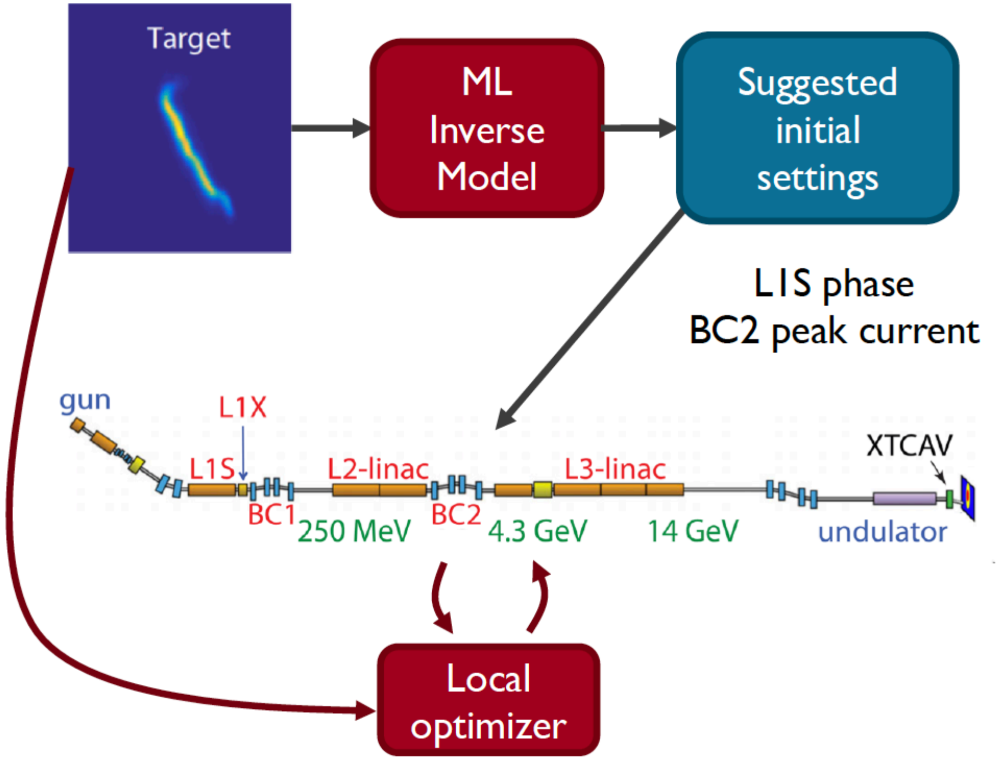


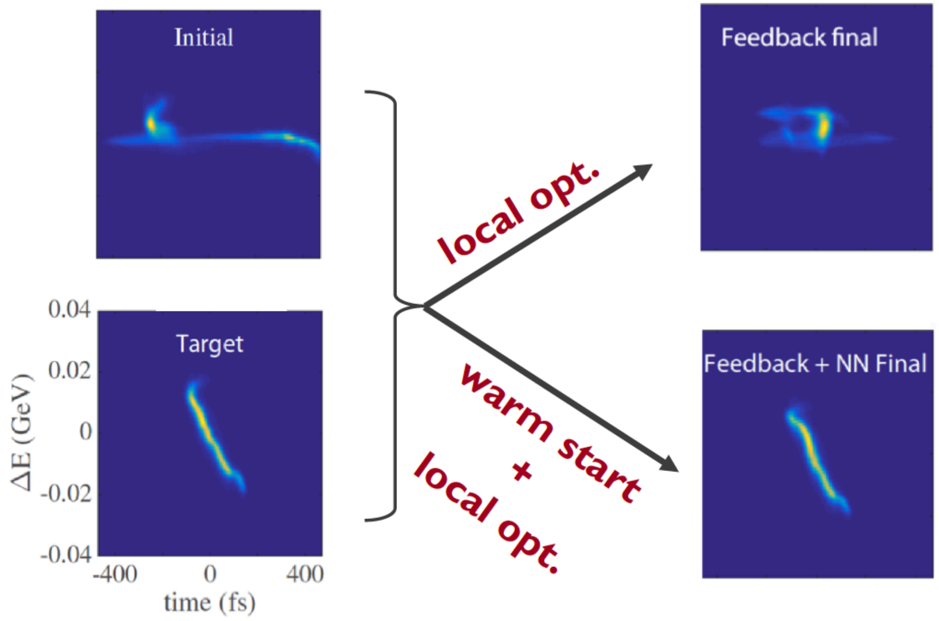


Required **130x fewer simulations** and had **10^6 times faster execution** in the optimization

A. Edelen, et al., PRAB 23, 044601 (2020)

Machine learning techniques enable rapid assessment and correction of machine settings to achieve desirable phase space parameters

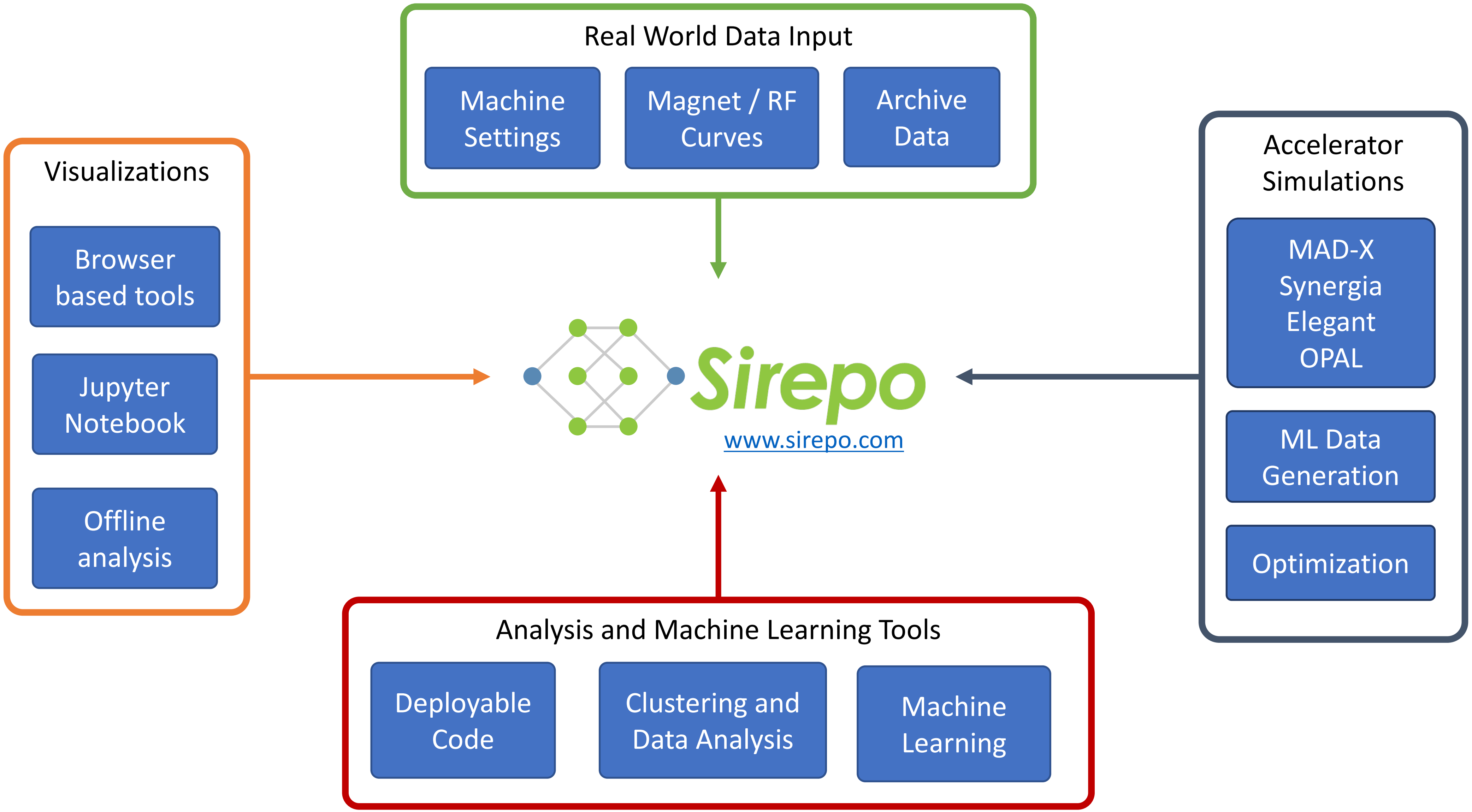




Local optimizer alone was unable to converge → **able to converge after initial settings from neural network**

A. Scheinker, A. Edelen, et al., PRL 121, 044801 (2018)

A controls toolbox powered by Sirepo



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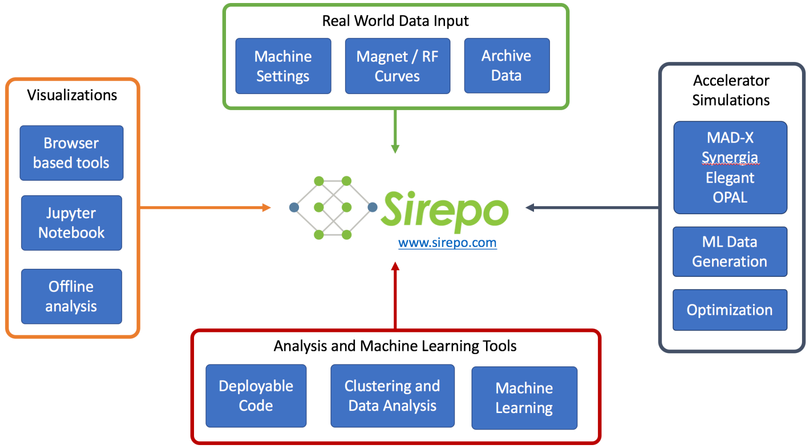
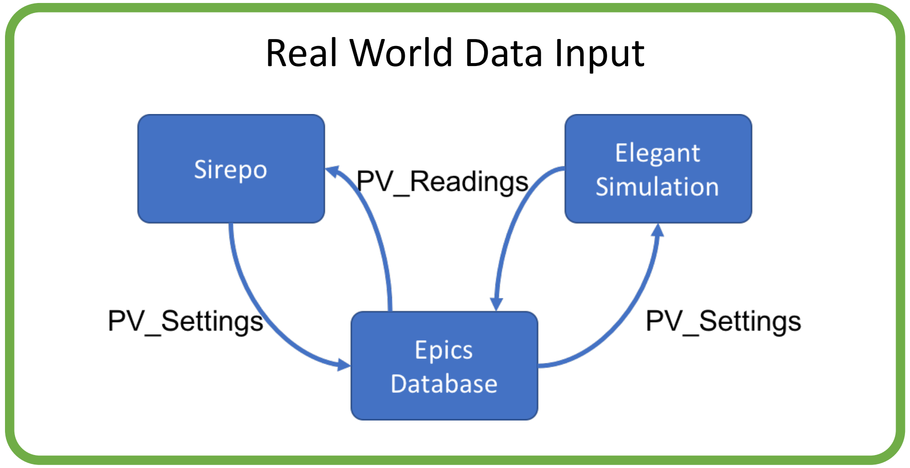




Analysis and Machine Learning Tools

Clustering
Data Import + Selection / Algorithm Selection / Cluster Identification / Advanced Visualizations

Curve Fitting
Equation Entry / Plotting / Fit Analysis / Higher Dimensional Fits

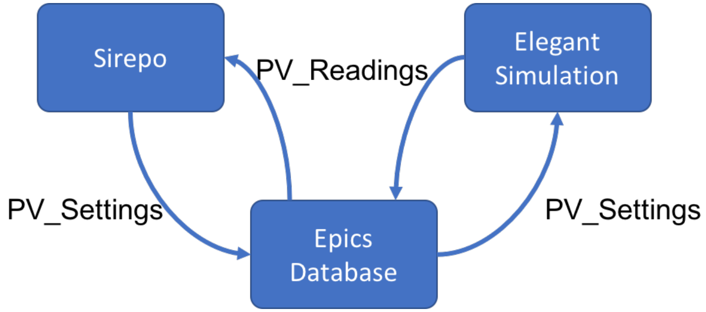
Frequency Analysis
1-D FFT / Peak Identification / 2-D FFT / Frequency Spectrograms

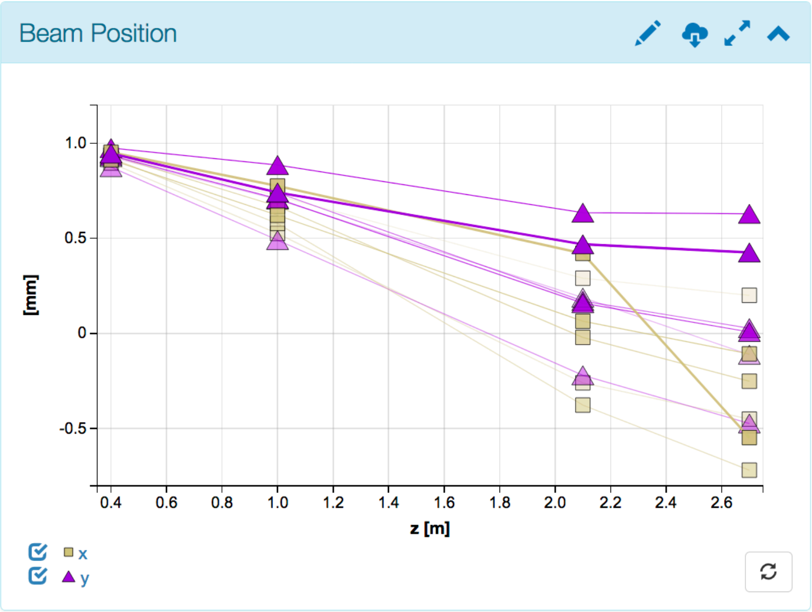
Data Import
Simulations / Machine Interface / Direct Import

Initial Data Visualization
Plotting Tools / Data Cleaning + Reduction / Splitting (training, test, validation)

Machine Learning Selection
Learning Paradigm / Model Selection + Construction / Loss Functions / Validation

Prototype web tools for controls





Prototype web tools for analysis and ML

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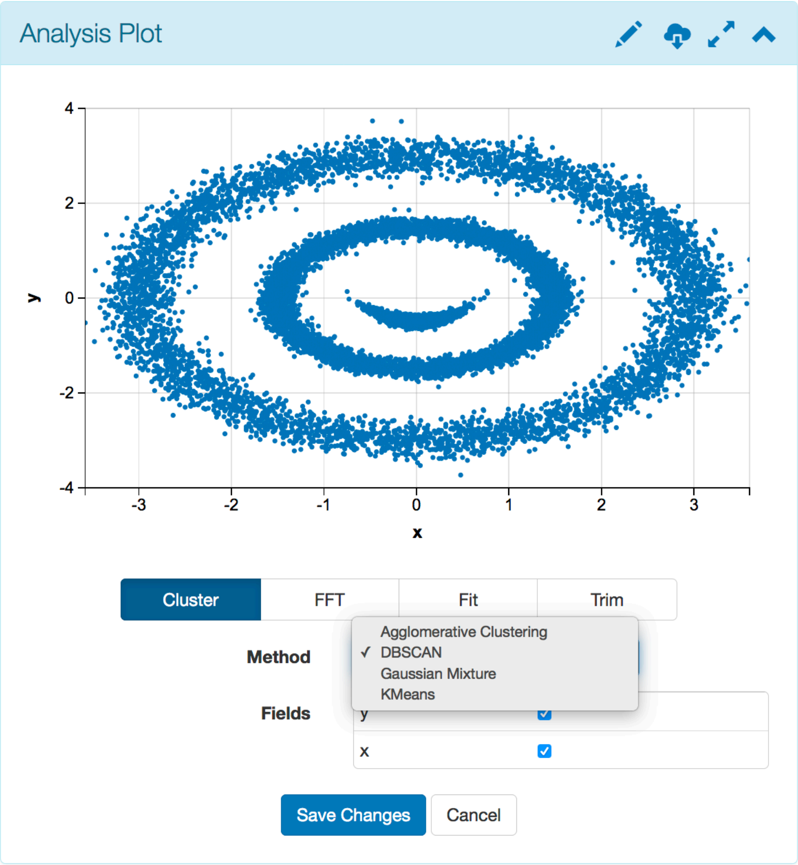

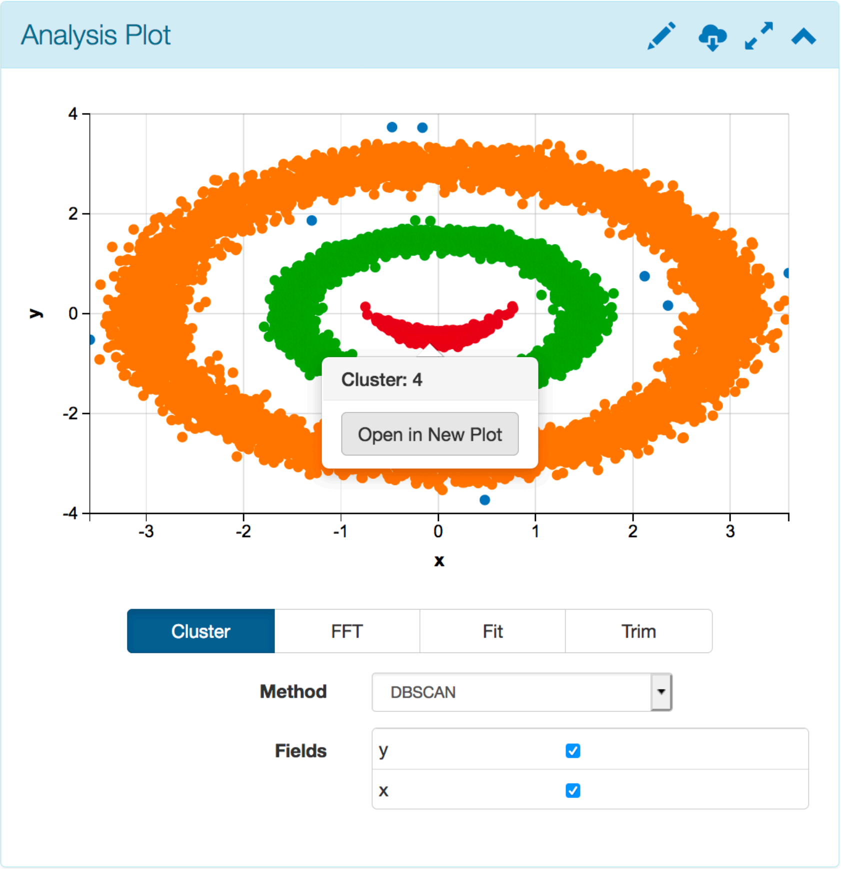

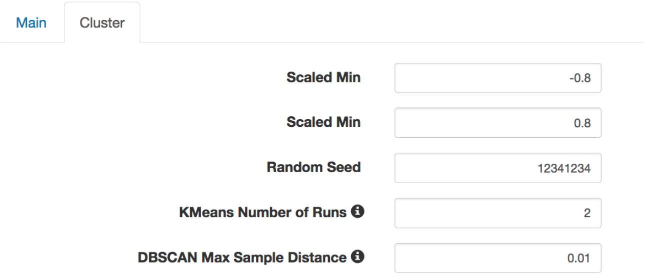

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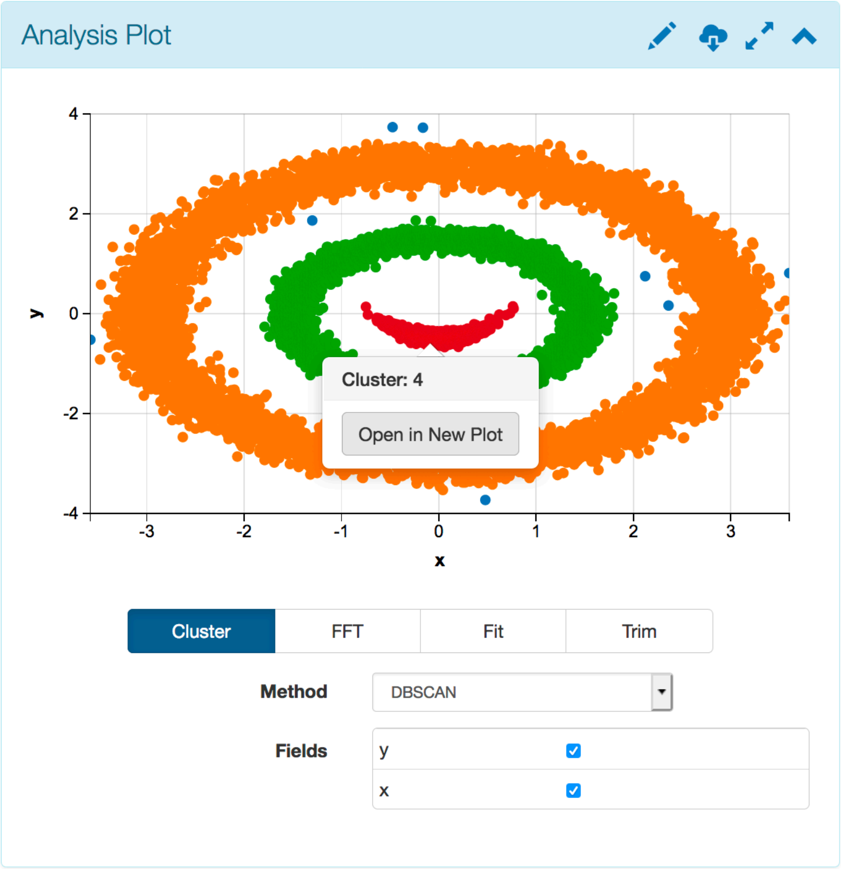

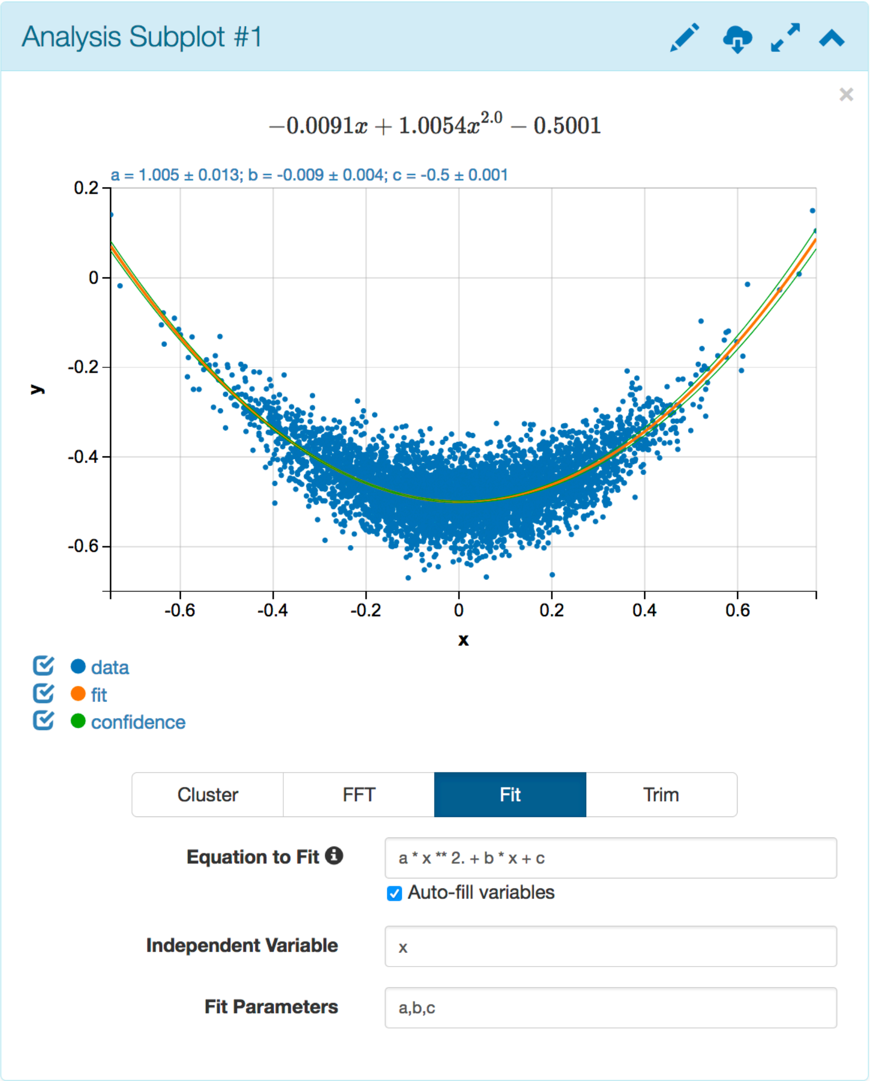

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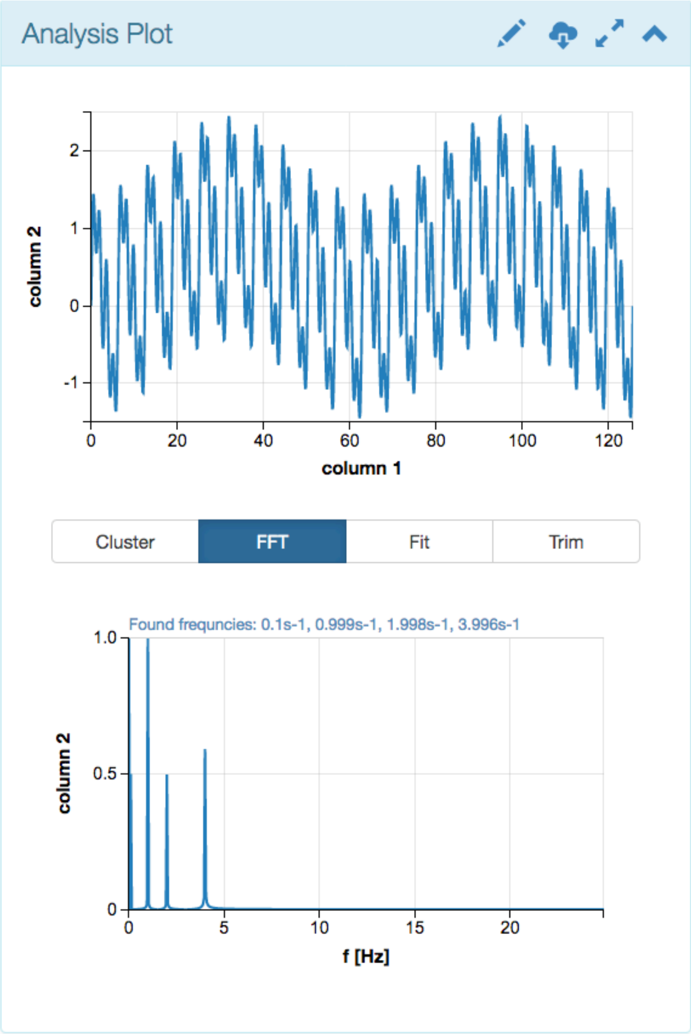

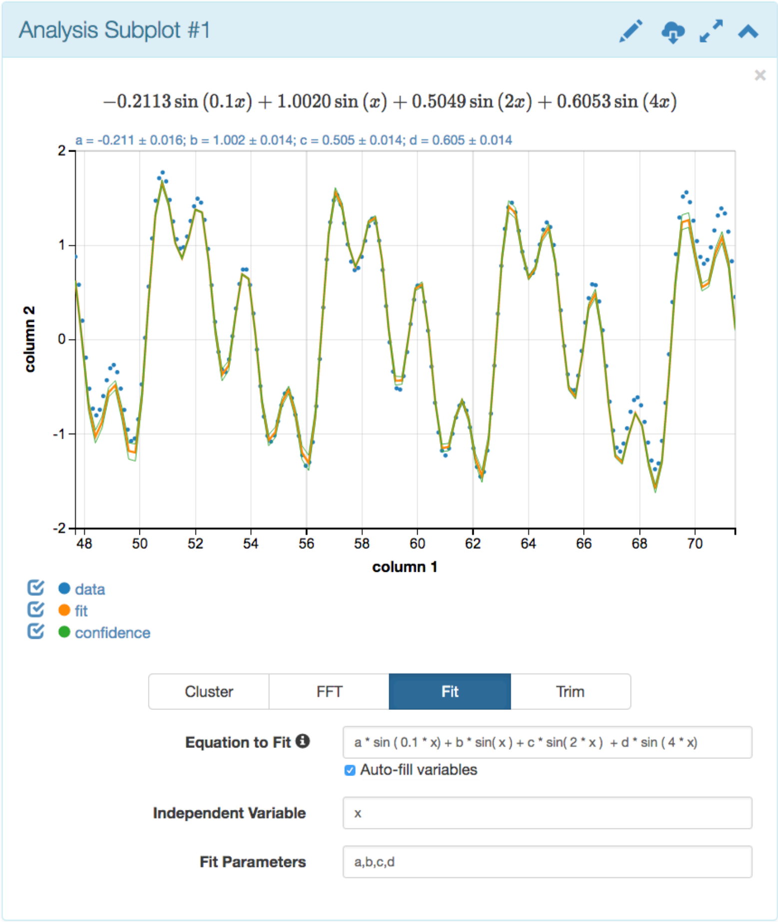

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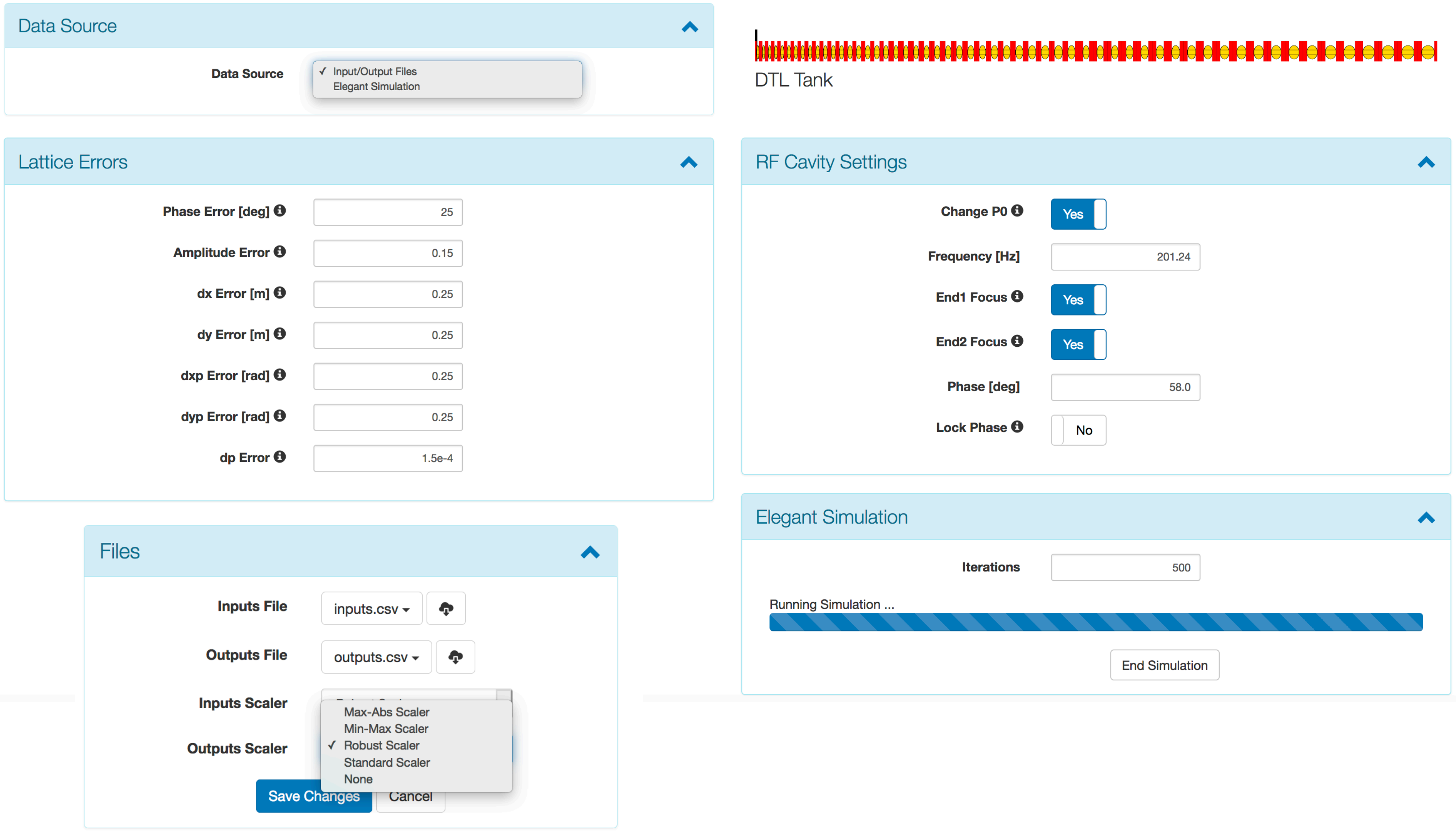

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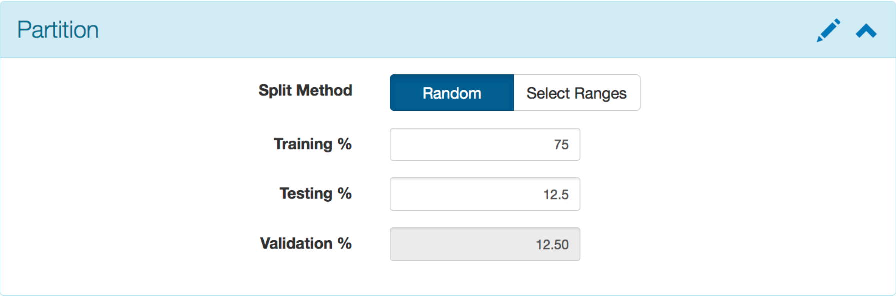

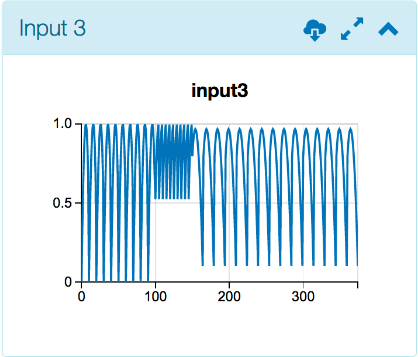

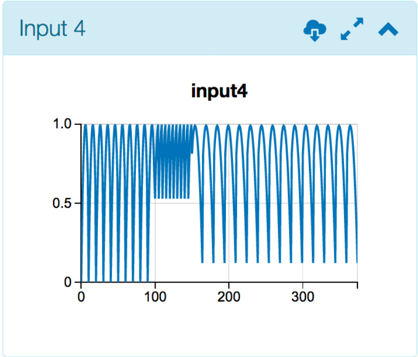

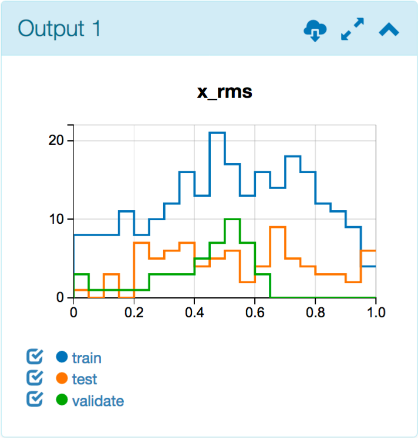

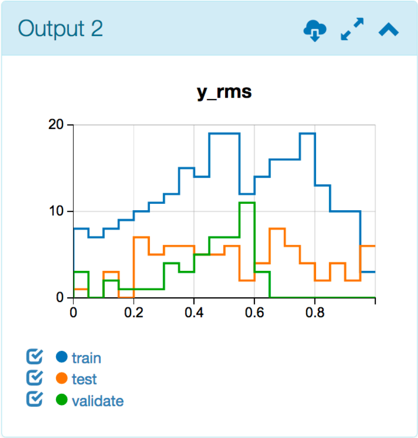

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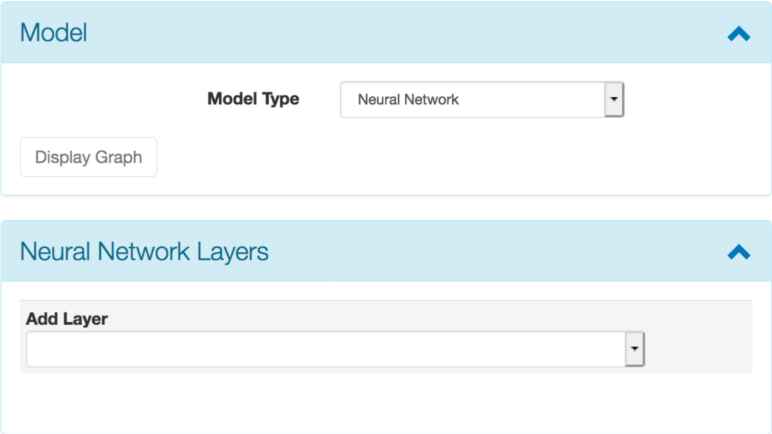

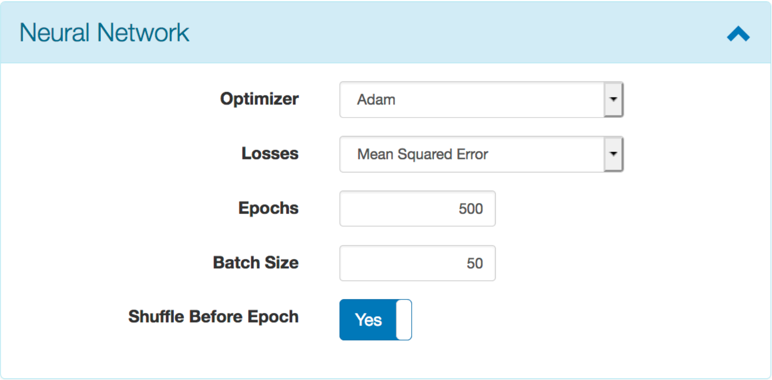

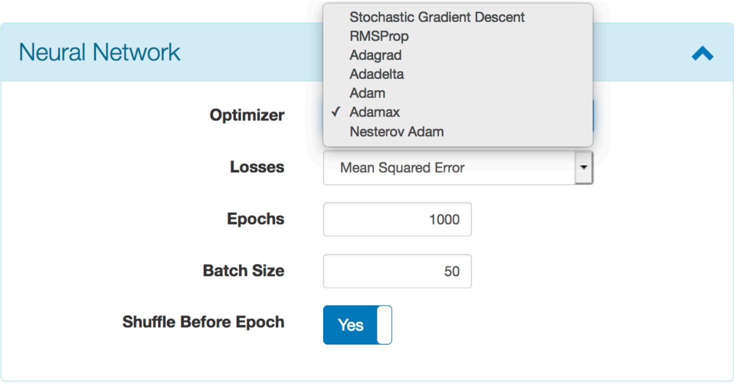

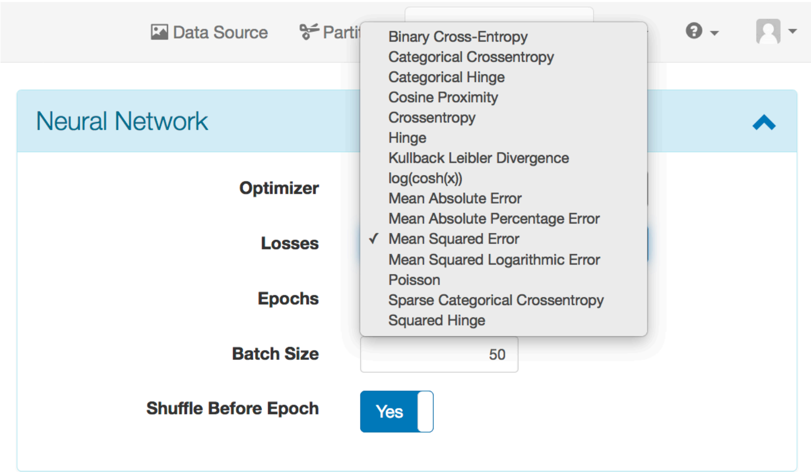

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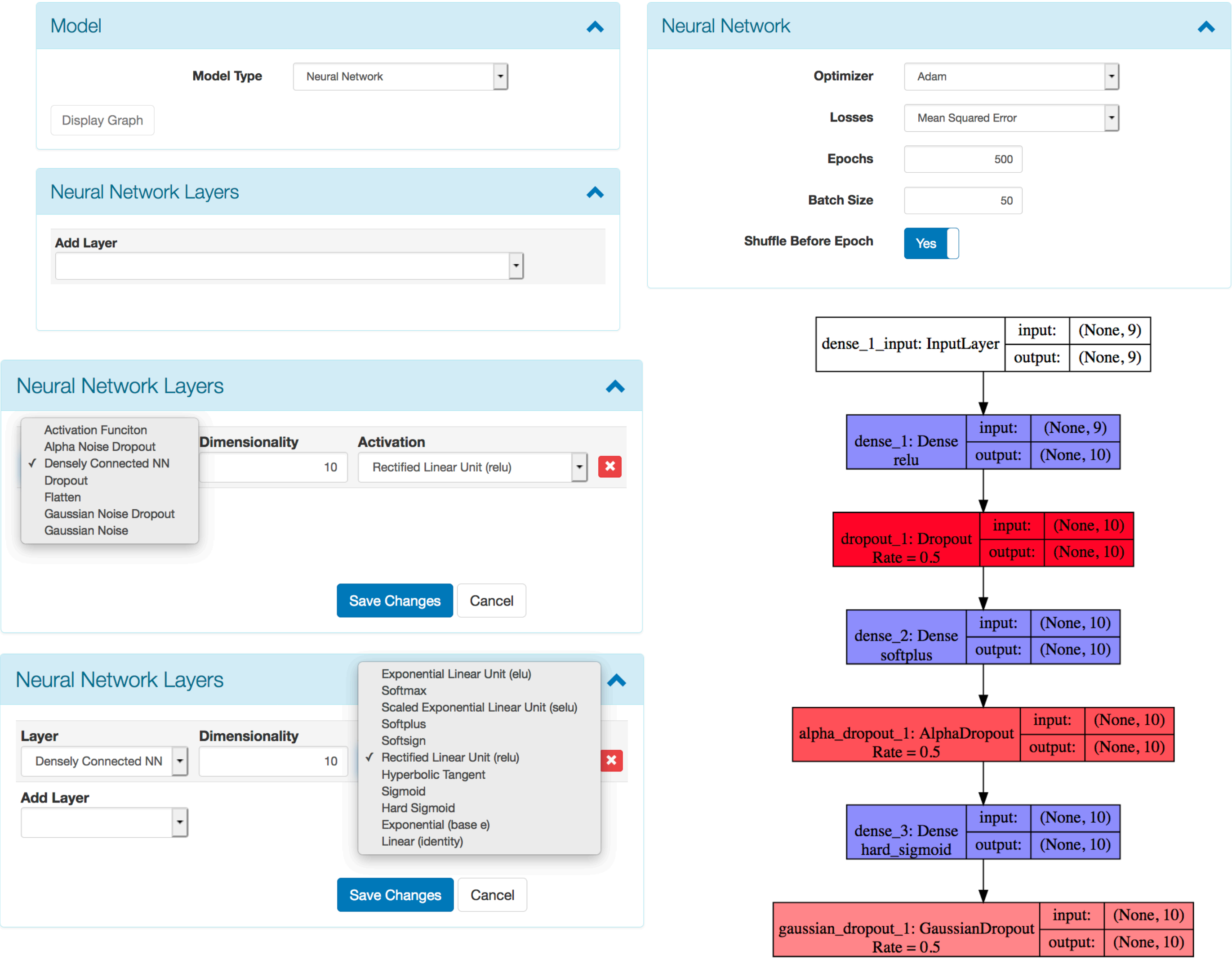

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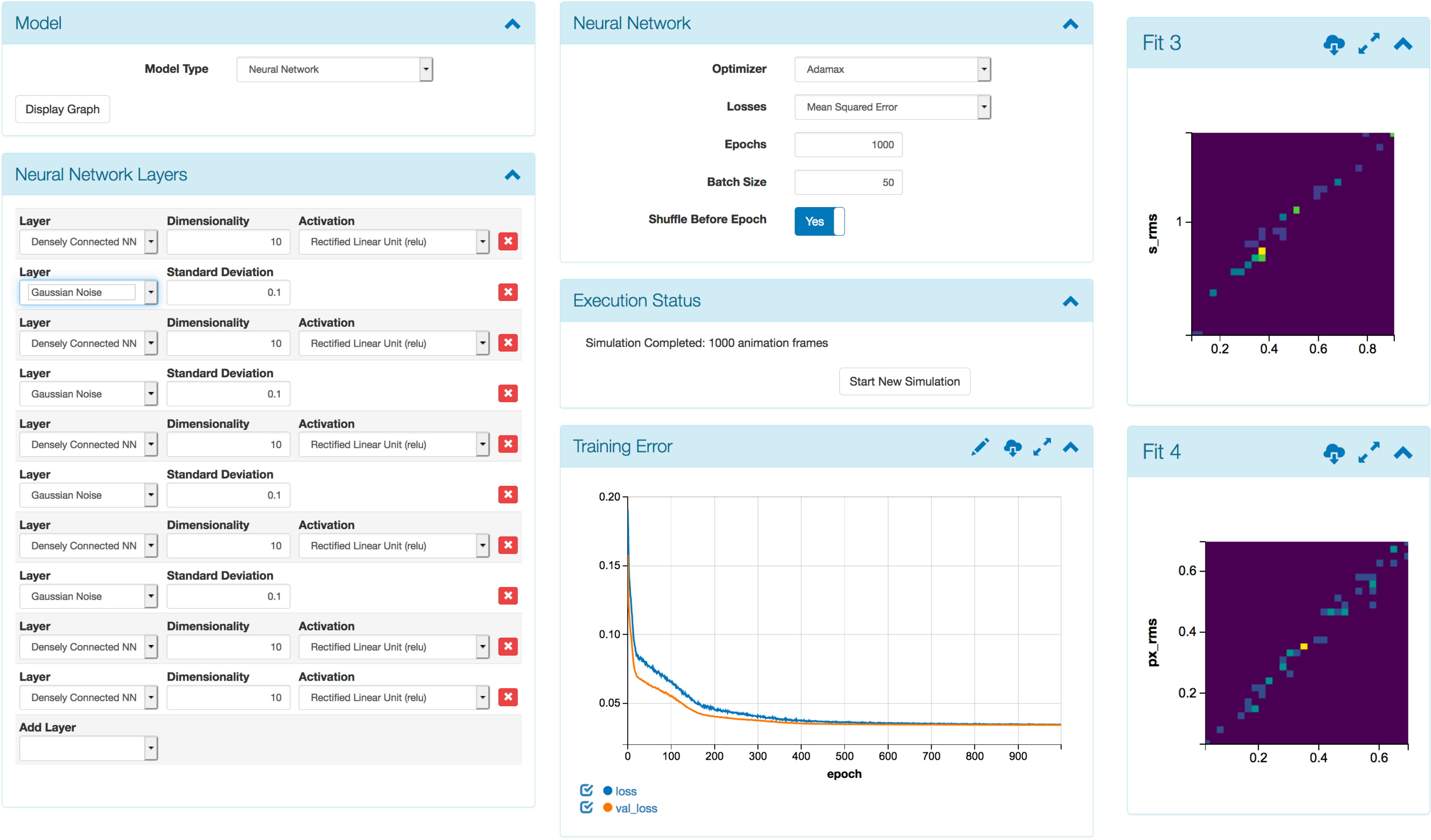
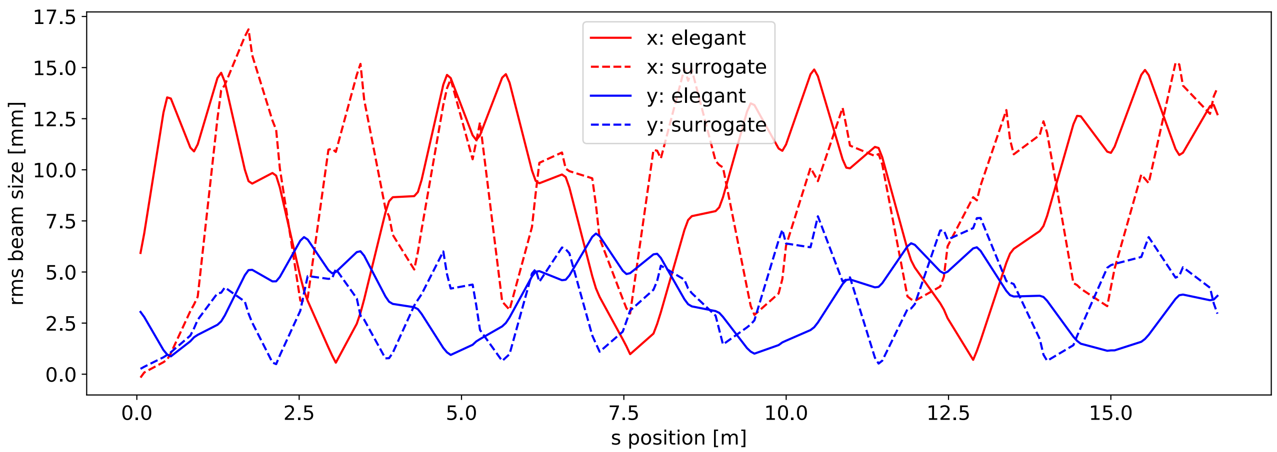
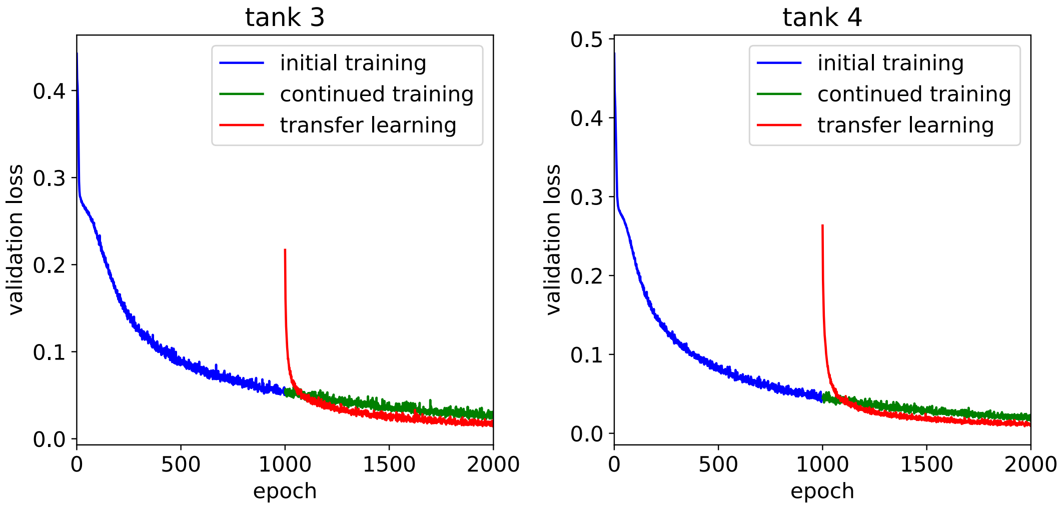
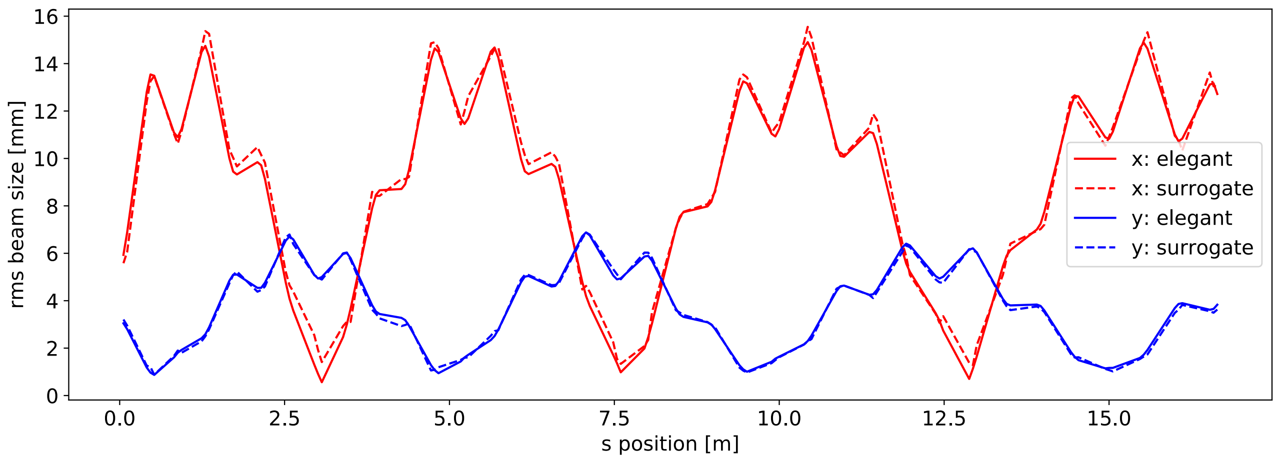


Transfer learning enables portable solutions between accelerators

- Case Study: The Fermilab linac
- Neural networks trained on data from DTL Tanks 2, 3, and 4 for 1k epochs
  - *Model from tank 2 is trained on data from tanks 3 and 4 for 1k epochs*
  - *Transfer learning trains faster and reaches a better overall solution*

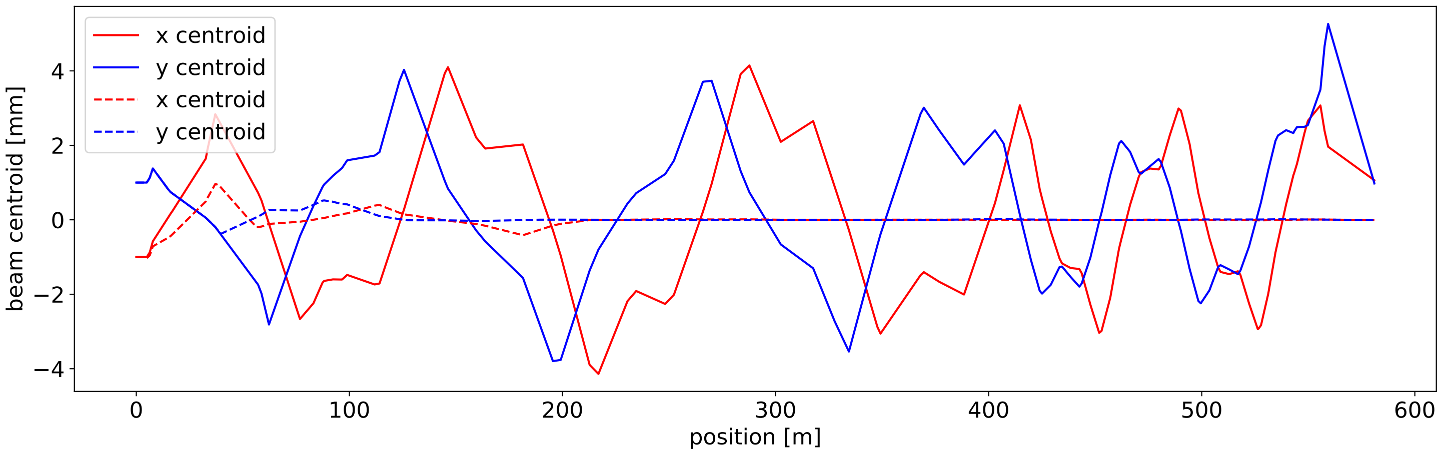




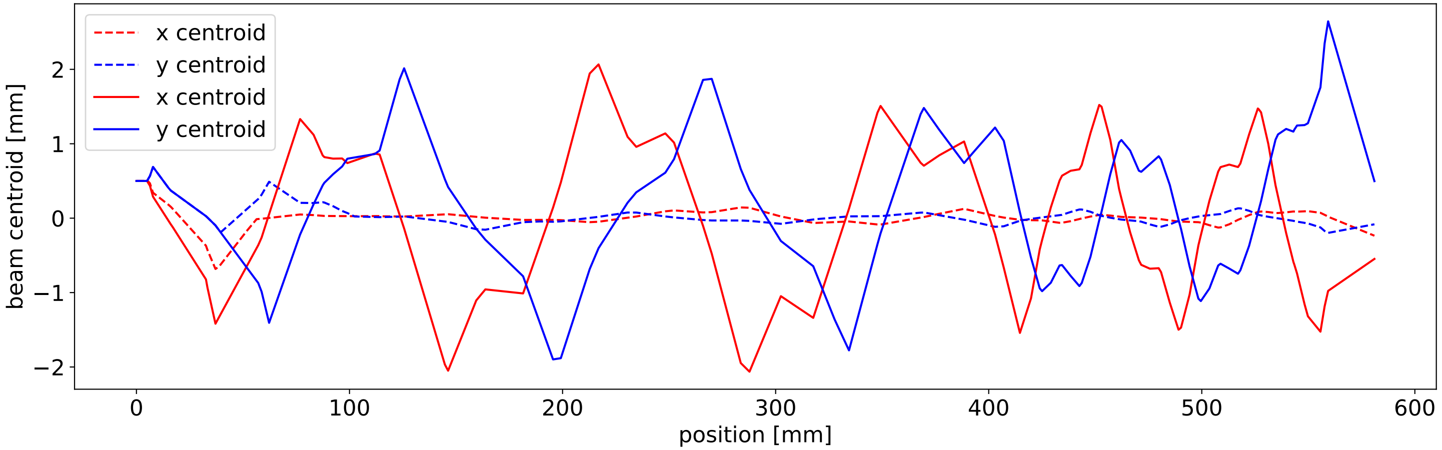


Inverse models for Beam steering in the ATR

- Optimization (top)
  - *Connect MAD-X simulation to python optimization tools using our middle layer*
  - *Study convergence rate for tuning the trajectory over a range of initial offsets*
  - *Direct optimization is time consuming on average took 2k iterations to converge*



- Machine Learning (bottom)
  - *Build inverse model of bpm-readings to corrector settings*
  - *Make feed-forward correction*
  - *Inverse models are fast and effective*
    - Single iteration generates a solution almost as effective as optimization



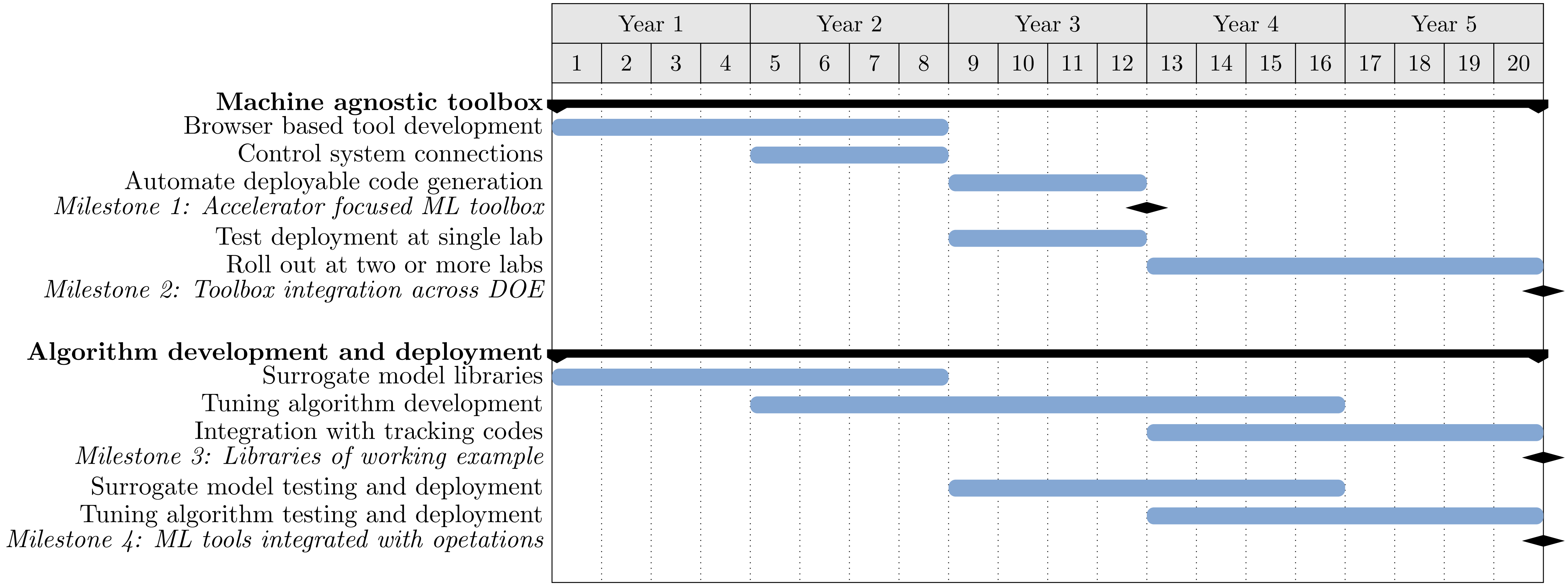
What are some of the challenges for ML and online tools?

- Machine Learning means data: but not just any data
  - *Carefully curated, archived, and cleaned*
  - *Large amounts of data can be required*

- Data rates are a potential challenge for browser based tools
- Data archiving
  - *Identifying correct parameters and ensuring time alignment or pulse ID*

- Machine models
  - *Many machines do not have up-to-date as-built models*
  - *Improving these models reduces demand on data-collection*
  - *It may not be possible to build models for old machines as survey data or field maps may not exist*

Roadmap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Machine agnostic toolbox
Browser based tool development
Control system connections
Automate deployable code generation
Milestone 1: Accelerator focused ML toolbox
Test deployment at single lab
Roll out at two or more labs
Milestone 2: Toolbox integration across DOE
Algorithm development and deployment
Surrogate model libraries
Tuning algorithm development
Integration with tracking codes
Milestone 3: Libraries of working example
Surrogate model testing and deployment
Tuning algorithm testing and deployment
Milestone 4: ML tools integrated with opetations

Our aim is to bridge gaps between accelerator facilities by developing machine agnostic tools that integrate machine learning, accelerator simulation codes, and accelerator operations

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