Element Aero

ADDING DATA SCIENCE AND MORE INTELLIGENCE TO OUR ACCELERATOR TOOLBOX

SANDRA G. BIEDRON, PH.D.

ELEMENT AERO

IPAC 2019 MELBOURNE AUSTRALIA

21 MAY 2019

Talk title was suggested to be "Machine Learning, Data Mining and Big Data Handling for Accelerators"

ELEMENT AERO

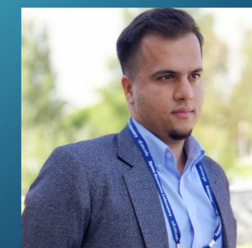
LET'S START WITH A STORY OF DATA FROM JUST A COUPLE OF YEARS AGO… *NAMES AND MACHINES REMOVED TO PROTECT THE INNOCENT*

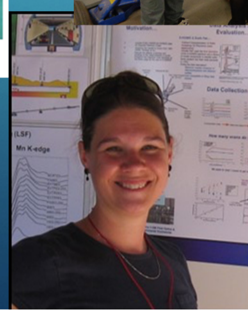
- A few of my high-energy physics friends were analyzing turn-by-turn data from an ion profile monitor. To do so, they had to manually save each set of profiles from each ramp, ~ 20MB. When they asked if they could get the control system to send them all the IPM data over the course of a few days the controls team reacted incredulously "But, that would be *gigabytes* of data. That sort of volume is impossible!" When the group told them that they were currently storing over a petabyte of experimental HEP data just across campus, they just acted like my friends were crazy.

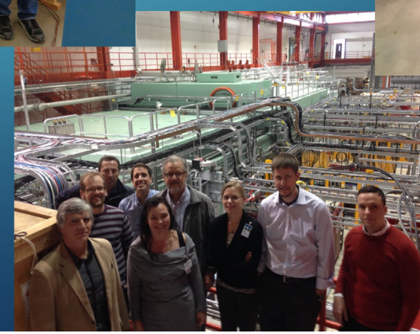
- Personally, I have been fortunate enough to work on all sorts of systems including controls, for laser and particle accelerator systems, aircraft for security applications, and for a directed energy demonstrator for a weapons system.
- Since 2002 I've been interested in more intelligent control and understanding. Why?
  - Simply - We need to make machines or systems better so we needed AI as a tool in ***some*** cases.
  - Since 2004 we have worked to demonstrate intelligent techniques as applied to among other things, particle accelerators.

PhD student Evelyne Meier (second from right) with (L to R): Edwina Cornish (Monash Deputy Vice Chancellor & Vice President Research), Greg LeBlanc and Sandra Biedron.

Some of first implementations of intelligent control done here at the Australian Synchrotron







Element Aero

TODAY

- General overview of intelligent methods of examining and using data.
- Pointing the audience to reference materials for recent workshops, resources of past efforts in related fields, and to recent initiatives for ethical design of intelligent systems (e.g. IEEE – see back-up charts).
- Mention a few examples of several applications of using intelligence and data in accelerators including in controls.
- Thoughts for how to better integrate data science processes into our future systems.
- Remind ourselves we cannot be decoupled from computing advances.

EXPLOSION IN DATA SCIENCE
(INCLUDING INTELLIGENT TECHNIQUES)

- In the last several years, more intelligent techniques have been used and have become available to help understand and use more exotic data sets.
- This has been enabled through the advances and accessibility of computing resources as well as in advanced algorithms.
- ***The particle accelerator community is now adapting these concepts to their systems. This includes the expanded use of high performance computing (HPC) resources.***

Element Aero

SERIES OF RECENT AND RELATED WORKSHOPS

- In the last fifteen months, four workshops have been held demonstrating the interest in artificial intelligence techniques as applied to particle accelerators as well as physics in general.
  - "**Intelligent Controls for Particle Accelerators,**" was held 30-31 January 2018 at Daresbury Laboratory www.cockcroft.ac.uk/events/ICPA/
  - "**ICFA Beam Dynamics Mini-Workshop: Machine Learning Applications for Particle Accelerators,**" was held 27 February-2 March 2018 at SLAC conf.slac.stanford.edu/icfa-ml-2018/
  - "**Physics Next: Machine Learning,**" was held by the American Physical Society Physical Review publications group in New York on 8-10 October 2018 https://journals.aps.org/physics-next/2018/
  - "**2nd ICFA Workshop on Machine Learning for Charged Particle Accelerators,**" was held from 26 February 2019 to 1 March 2019 at PSI https://indico.psi.ch/event/6698/

AND BE ON THE LOOKOUT

- For a report from a recent Department of Energy/Department of Defense/National Institute of Health/Department of Homeland Security workshop that will help guide research priorities for accelerators for several applications in security and medicine
- **"Basic Research Needs Workshop on Compact Accelerators for Security and Medicine"**
- https://www.orau.gov/brncasm2019/default.htm
- Report due to be released in August
- Section on **Design, Computing and Controls** co-led by John Cary (Tech-X and University of Colorado Boulder) and me along.
- One take home message from the workshop was that there is ***already*** a shortage of 5000 x-ray treatment machines (shown graphically yesterday by Suzie Sheehy in the world map).
- Better reliability and ease of operation can help make compact accelerators a reality! BUT WE NEED DATA SCIENCE (and systems engineering).

EXAMPLES AT THIS CONFERENCE, AT IPAC2018 AND IN HEP

- IPAC 2019
  - This morning – Anna Solopova, JLAB, “SRF Cavity Fault Classification Using Machine Learning At CEBAF”
  - G. Azzopardi, “Operational Results of LHC Collimator Alignment Using Machine Learning” – Today at 15:00
  - Posters: MOPGW017, MOPGW023, MOPGW026, THPRB003, THPRB011, THPRB040, THPRB077, THPRB102, THPRB106, THPTS047, TUPGW094, WEPGW045, WEPGW049, WEPGW058, WEPGW081, WEPGW081, SUSPF076, …
- At IPAC 2018
  - Talk THYGBE http://ipac2018.vrws.de/talks/thygbe2_talk.pdf (A. Edelen)
- In HEP
  - 18 Workshops in ML for HEP between 2015-2018 See list in Promise and Challenges of Machine Learning in Particle Physics, Astrophysics, and Cosmology Kyle Cranmer (New York University) https://cdn.journals.aps.org//cf3bab2e-015c-4eac-813a-570bc512c5e9/KyleCranmer.pdf

ACCELERATOR TOOLBOX

PHYSICS, CHEMISTRY, MECHANICAL ENGINEERING, ELECTRICAL ENGINEERING, ETC.

ELEMENT AERO

- Materials science
- Vacuum science
- Collective effects
- Electromagnetism
- Vacuum electronics/RF sources
- Instrumentation
- Controls engineering
- Computational techniques

- Lasers
- Radiation and dosimetry
- Pulsed power
- Survey and alignment
- High performance computing
- Data science, including mathematical optimisation and machine learning
- Etc…

Since we as a community already have such a filled skill set (toolbox), this may have led to a slow adaptation of data science as we thought we could solve problems in other ways (already in our toolbox). (Remember the GB versus PB story…and other examples)

ACCELERATOR TOOLBOX

ELEMENT AERO

PHYSICS, CHEMISTRY, MECHANICAL ENGINEERING, ELECT… ETC.

- Materials science
- Lasers
- Vac…

One of the hard parts of examining data is that one needs to understand where the data comes from and what it means. **The data is not disconnected from the system from which it originates.**

This makes choosing the right data science tools for each accelerator "challenge" difficult. Why? Our toolbox of systems is so large and so integrated/overlapping so the data science techniques have to be chosen very carefully.

This means that a data scientist cannot just walk in off the street from a different field. **The solutions we need are accelerator-domain specific, complicated, chosen by experience, and are in no way a single, magic band-aid.**

Etc…

…ince we as a community already have such a filled skill set (toolbox), this may have led to a slow adaptation of data science as we thought we could solve problems in other ways (already in our toolbox). (Remember the GB versus PB story…and other examples)

Element Aero

Data Science

Not any one simple definition fits all

- Encompasses its own toolbox of skills
  - Knowledge of where the data originates (in data science terms "its domain")
  - Exploratory data analysis
  - Mathematics
  - Statistics
  - Machine learning
  - Optimization
  - Visualization
  - High performance computing
  - Deep learning
  - Specialized computer hardware – FPGAs, application-specific integrated circuit (ASIC), including tensor processing units (TPUs), neural engines
  - Etc…

ELEMENT AERO

DATA SCIENCE

NOT ANY ONE SIMPLE DEFINITION FITS AL

- Encompasses its own to

One of the things to keep in mind when thinking about which algorithms to use is that the people that developed a certain algorithm were concerned about making a better algorithm and not about your exact data set. The algorithm might have been developed on random data.

We accelerator people, on the other hand have "more interesting" data sets, including errors in data and embedded physics.

There might not be just one answer to the data science approach, but be wise in your approach(es).

- GAs, application-specific integrated circuit (ASIC), including tensor p), neural engines
- Etc.

DATA SCIENCE CONTINUED

ALL THE WORDS YOU HEAR IN THE NEWS

Element Aero

Numerical Analysis

- Optimization (including genetic algorithms)
- Interpolation, extrapolation, and regression
- Systems of equations
- Eigenvalue and singular value problems
- Numerical differentiation
- Numerical integration
- Etc.

Artificial Intelligence (AI)

Techniques that enable artificial systems (computers) to mimic human intelligence using logic, if-then rules, decision trees, machine learning, and deep learning.

Machine Learning (ML)

A subset of AI that includes the use of complex statistical algorithms to improve performing tasks as experience Increases.

Deep Learning

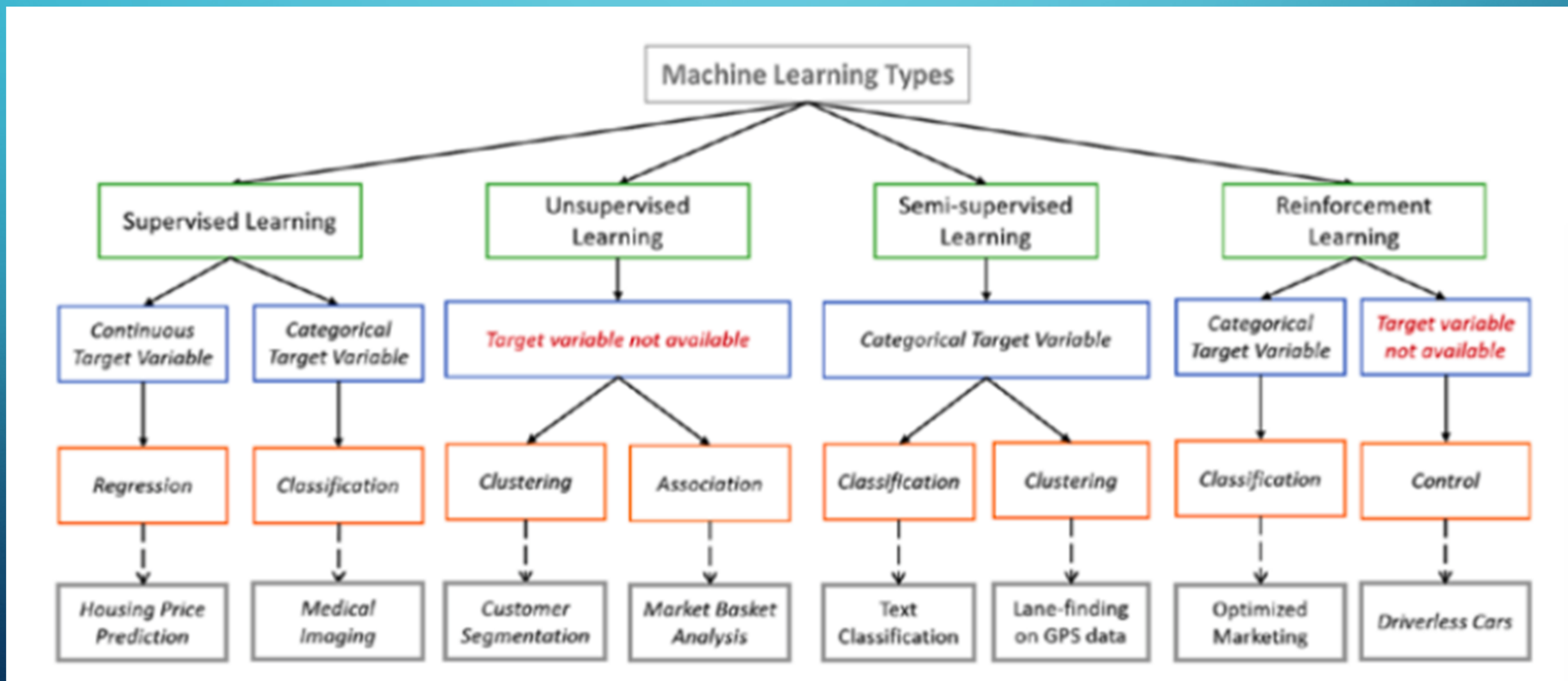
A subset of ML with algorithms to allow software to train itself to perform tasks such as image recognition through multilayered neural networks.

"[Machine Learning is the] field of study that gives computers the ability to learn without being explicitly programmed." - Arthur Samuel in 1959

MACHINE LEARNING

ELEMENT AERO

- Machine learning is a data analysis method that can identify patterns, learns from them and utilizes for making accurate predictions and better decisions without or with minimal human guidance.



ELEMENT AERO

SO WHAT ABOUT ACCELERATORS AS INTELLIGENT SYSTEMS?

- How can we best use data science to better design, control, and understand our machines?
  - *AI/Intelligence is **one way** and it is more than just algorithms, it is data, sensors, computing platforms and analysis techniques! (Stated succinctly by J. Amundson, Fermilab)*

WHAT ARE THE MOST POWERFUL WAYS TO EXAMINE DATA FROM ACCELERATORS?

Element Aero

- There are many steps to properly examine and use/apply data.
- We can use techniques such as mathematical optimisation or machine learning.
- For machine learning (maybe better called machine training*…) we need good data on which to learn/train.
- BUT - We also only want to use these techniques where they are actually required/appropriate. (Just because you can do it does not mean you should.)

*The difference between training a horse, for instance, and a machine is that we have control over the systems engineering architecture of the machine itself and the algorithms but not in the case of the horse.
I'll come back to this in a bit.

Element Aero

HOW DO WE GET THERE?

- WARNING! – Data science is not a magic black box. **It is not magic.** It is just another tool that like all of our tools, can be powerful if implemented properly. (one way is through AI)


“What we really need in AI
is someone who has super powers.”

Element Aero

STEP 1. GET THE DATA

- We need to gather the data from our challenging accelerator or accelerator sub-system(s).
- This can be difficult as in especially challenging cases, you might not collect the correct data OR maybe you think something is outside the possibility of influencing a sub-system (so data not logged or not even monitored from this source).
- Make certain you collect (or generate if simulation only) enough data.

STEP 2. DATA PREPARATION

- May not need if you are doing more traditional data analytics not involving AI/machine learning.

REDUCE THE NUMBER OF FEATURES

A dataset can contain a large amount of features associated with it.

Reduction in features essentially summarizes the data, playing an important role in being able to apply techniques of data science.

Why do we need to do this? EXAMPLES

- Help reduce the computation or training time by algorithms.
- Preserve limited storage space.
- Permit use of some algorithms that do not perform well with large dimensions.

- Removes redundant features (reduce multicollinearity).
- Reductions helps in visualizing data (as reducing to 2D or 3D may permit plotting and observing patterns more clearly.

DIMENSIONALITY REDUCTION

- Formally - Dimensionality reduction is the process of reducing the number of random variables under consideration. Through reduction, one obtains a set of principal variables.
- Algorithms like Principal Component Analysis, Linear Discriminant Analysis, Random Forest, Single Value Decomposition, Missing Value Ratio, Low Variance Filter, High Correlation Filter, Backward Feature Elimination, Forward Feature Selection, Independent Component Analysis, Factor Analysis, Methods Based on Projections, Uniform Manifold Approximation and Projection (UMAP), t-Distributed Stochastic Neighbor Embedding (t-SNE) can be used to reduce the dimensionality.
- Again, such reduction will improve the results of, for instance, classification with a neural network.

Element Aero

SPLITTING THE DATA

- Need to split the data into two separate pots - training and evaluation data.
- You want to train your model on the training data and then evaluate the model's effectiveness through the evaluation data.

ELEMENT AERO

STEP 3. CHOOSE A LEARNING METHOD

- Choose a learning (training) method that is appropriate from the many that exist already suited to your data (image, text, numbers, etc…)
- Again – this is not a black box. Many algorithms and infinite combinations

Element Aero

STATISTICAL EXAMINATION OF THE DATA

We need to realize that not all the data we collect makes sense in terms of volume, type, or if there are errors.

- Mean average - determines overall trend of a data set
- Standard deviation - the spread of data around mean
- Regression - examines relation between variables
- Outlier detection & treatment - used where noise is present
- Support Vector Machines (SVM) based anomaly detection
- Clustering-based anomaly detection
- Hypothesis Testing

Element Aero

STEP 4. ALLOW THE MACHINE TO LEARN

- Build a candidate model from the data using the selected learning method.
- This can take many iterations.
- NOTE unsupervised ML models have the ability to self-learn patterns to deliver answers even when input data is unlabeled and has unknown outcomes.

“All models are wrong, but some are useful” George E. P. Box

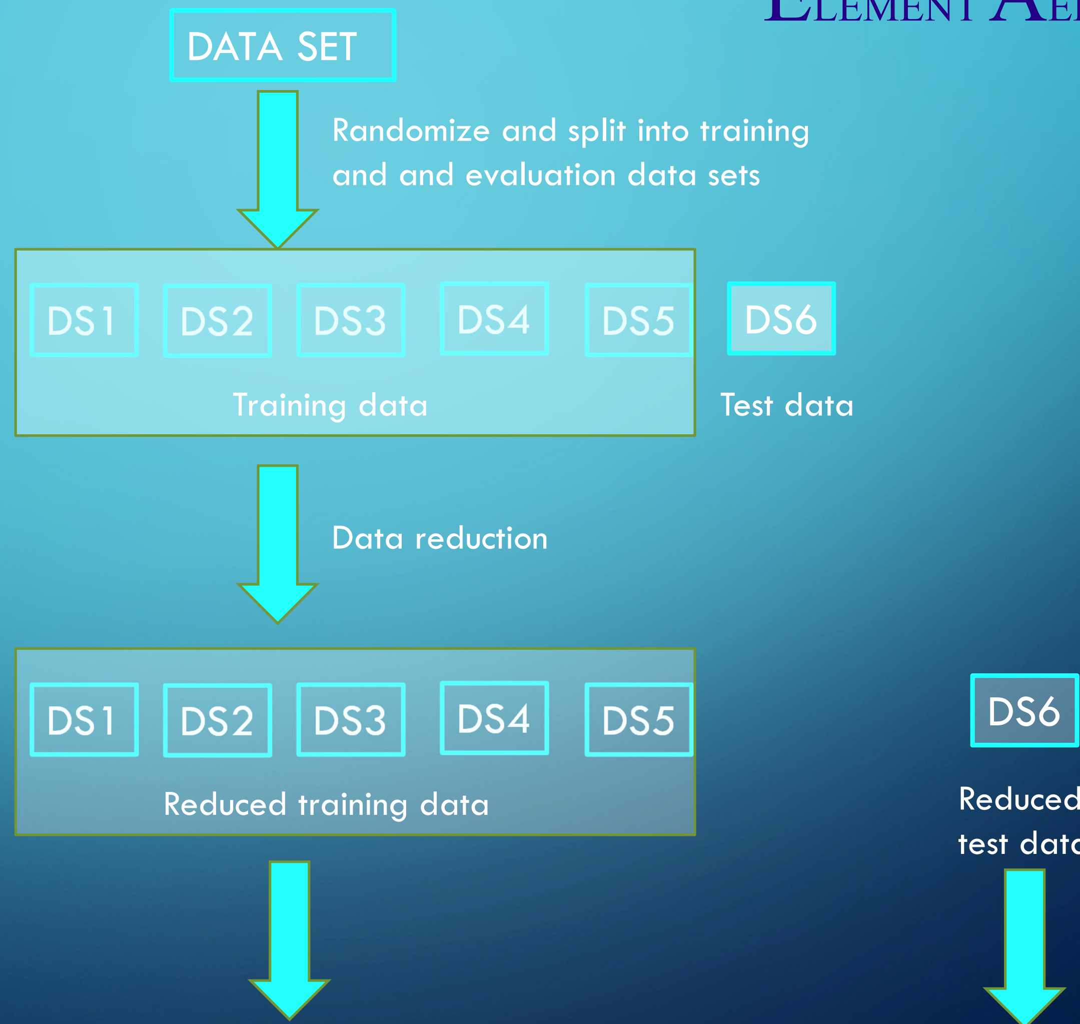
STEP 5. EVALUATE

- Test your model on the evaluation data.

STEP 6. REFINE THE MODEL – TUNING STEP(S)

7. PREDICTION OR USE STEP!

Element Aero



Element Aero

Select informative voxels and determine any optimal parameters

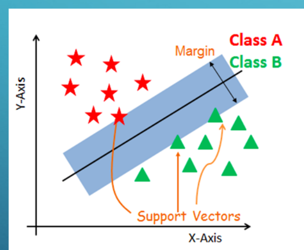
DS1 DS2 DS3 DS4 DS5

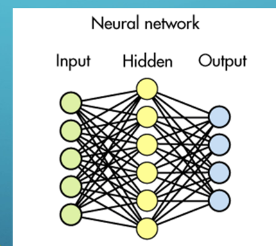
Ready training data

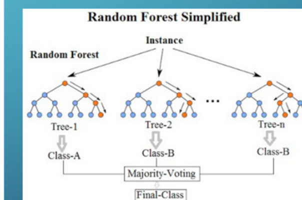
DS6

Reduced test data

Model building (e.g. Decision Trees, Neutral Networks, Linear regression, Bayesian networks, Nearest Neighbor, Support Vector Machine)







Test model

Evaluation

Repeat as necessary

Element Aero

A FEW EXAMPLES

- A few examples recently exploiting intelligent methods and HPC applied to particle accelerators.

Simulations and HPC are central to the APS Upgrade (M. Borland)

- Massively parallel multi-objective genetic optimizer to develop physics design
- Design of complex multi-function magnets using 3D codes
- Simulation of collective behavior of high-charge, multi-bunch electron beams
- Simulation of vacuum system performance in response to synchrotron radiation
- Simulation of commissioning and operational performance
- Understanding and pushing intensity limits in the injector complex
- Prediction of radiation levels and shielding requirements

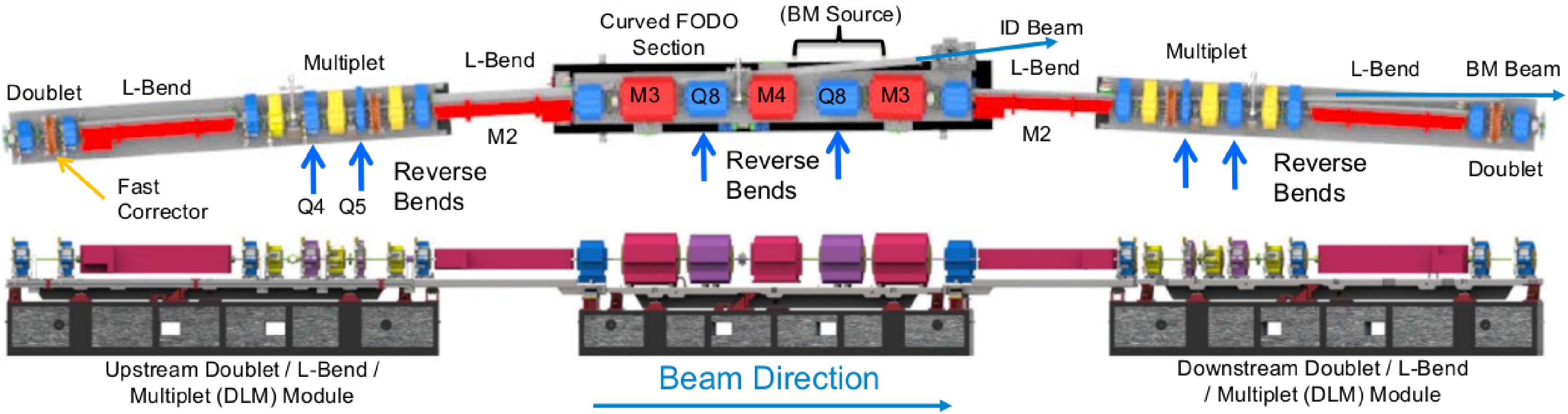


Image courtesy G. Decker, APS-U

Courtesy M. Borland Argonne

HPC saves money in the end, but often underutilized

- To reduce design costs, HPC is essential
  - Provide high-fidelity models with fewer compromises, leading to fewer (often no) iterations with hardware prototypes
  - Make best use of expensive engineering and physics staff
  - Provide robust statistical data on expected performance
- Common reasons HPC is underutilized
  - Staff not trained to use HPC systems and software
  - Software chosen for familiarity and convenience, not HPC capabilities
  - Management undervalues computation, fails to provide access to HPC systems and support
- Example: APS upgrade beam physics effort provided with ~60M core hours per year on ANL internal computing clusters, excellent support
  - In early years, also given access to ALCF resources (not needed now)
  - Similar resources being devoted to ALS Upgrade

Argonne NATIONAL LABORATORY

Courtesy Jean-Luc Vay, LBL

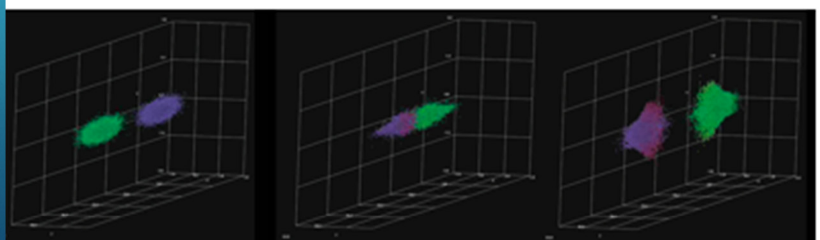
Extreme computing enables detailed beam & accelerator science

Parallel Luminosity Optimization in conventional accelerator

Code: BeamBeam3D + optimizer

Time-to-solution:

- **serial code & optimizer:** ~35 years
- **Parallel code & optimizer:** ~1 day

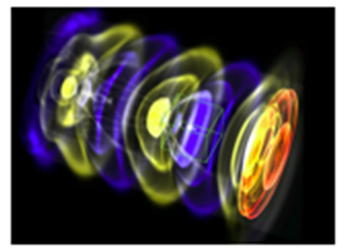


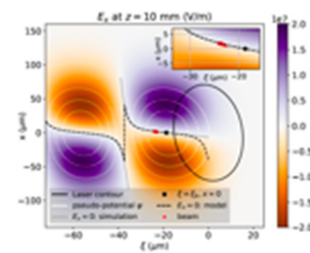
Study of pulse front tilt in laser-plasma accelerators

Code: WarpX

Time-to-solution (largest run):

- **serial code in lab frame:** ~500 years
- **Parallel code in boosted frame:** ~4 h





Computer: Cori at NERSC – 9,688 nodes, 658,784 cores.

PACMAN: Particle Accelerators & Machine Learning

Co-PIs:	Jochem Snuverink (PSI), Tatiana Pieloni (EPFL),
Partner(s):	Andreas Adelmann, Markus Janousch, Davide Reggiani (PSI)
	Olivier Schneider (EPFL), Anastasia Pentina (SDSC)
PostDocs & PhDs:	Jaime Coello, Loïc Coyle, Sichen Li, Michael Schenk

SDSC
EPFL
PAUL SCHERRER INSTITUT PSI

Problem :
Utilising ML to operate particle accelerators *safely* (LHC and HIPA):

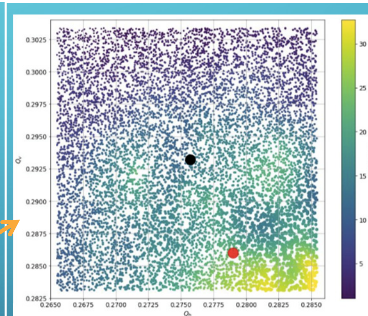
A. Minimise beam losses
B. Better control of accelerator parameters
C. Prevent unnecessary machine interruptions
D. Improve beam dynamics modelling

Solution: Two Tier Model

1. Construct surrogate models from data and sim.
2. Apply surrogate models to online operation and compare to predictions

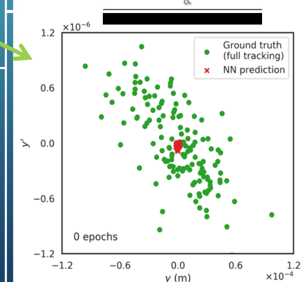
Several lines of attack:

A. Safe Bayesian Optimisation
B. Surrogate models to enhance performance
C. Prognostics to detect changes in the system
D. Neural networks instead of particle tracking



Beam lifetime

Nominal
Optimised



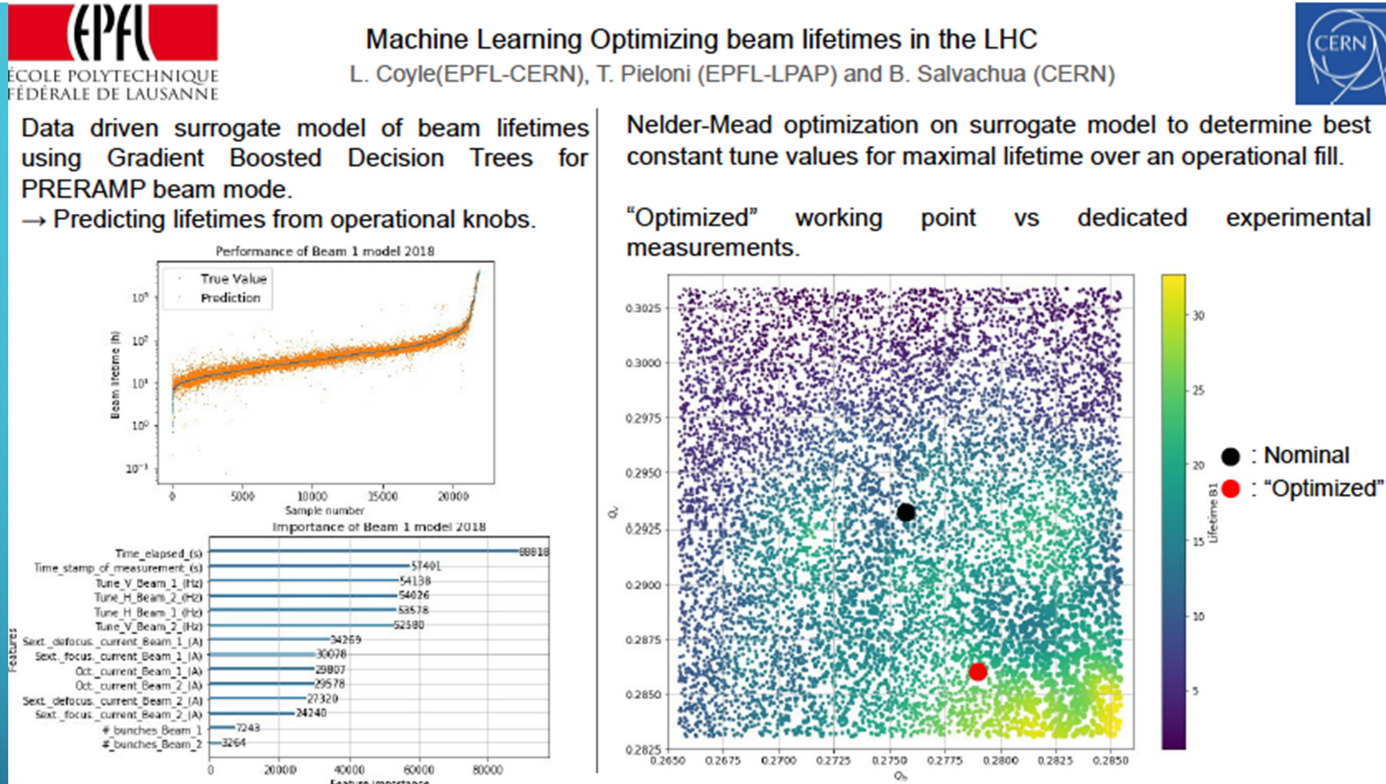
NN tracking training

phase space after 1 turn

speedup factor: 20 x

Impact:

- Safe and improved operation
- Reduced component damage
- Increased uptime
- Improve or change future accelerator design
- Optimise data storage for ML



- LHC beam lifetime _> With the LHC physics fills of 2018 year they built a surrogate model of the LHC at injection energy. With that model they determined the best working point (RED DOT). Then they did and experiment scanning the various parameters they had in the model and measured lifetimes (color code points). The yellow area is where the lifetime is the highest and also the prediction of the surrogate model. They believe larger emittances in some cases because of collective instabilities that the trained model did not have (thus a small yellow area).

Courtesy of Jochem Snuverink

ANNA **SOLOPOVA**

- SRF Cavity Fault Classification Using Machine Learning At CEBAF

Results

	Machine Learning			Deep Learning
Problem	Which Cavity?	Which Fault?		Which Fault?
Feature Engineering	*tsfresh*	*tsfresh*	auto-regression	*none*
Model	Random Forest	Decision Tree	Random Forest	RNN-LSTM *
Result	95.7%	96.6%	88%	86%

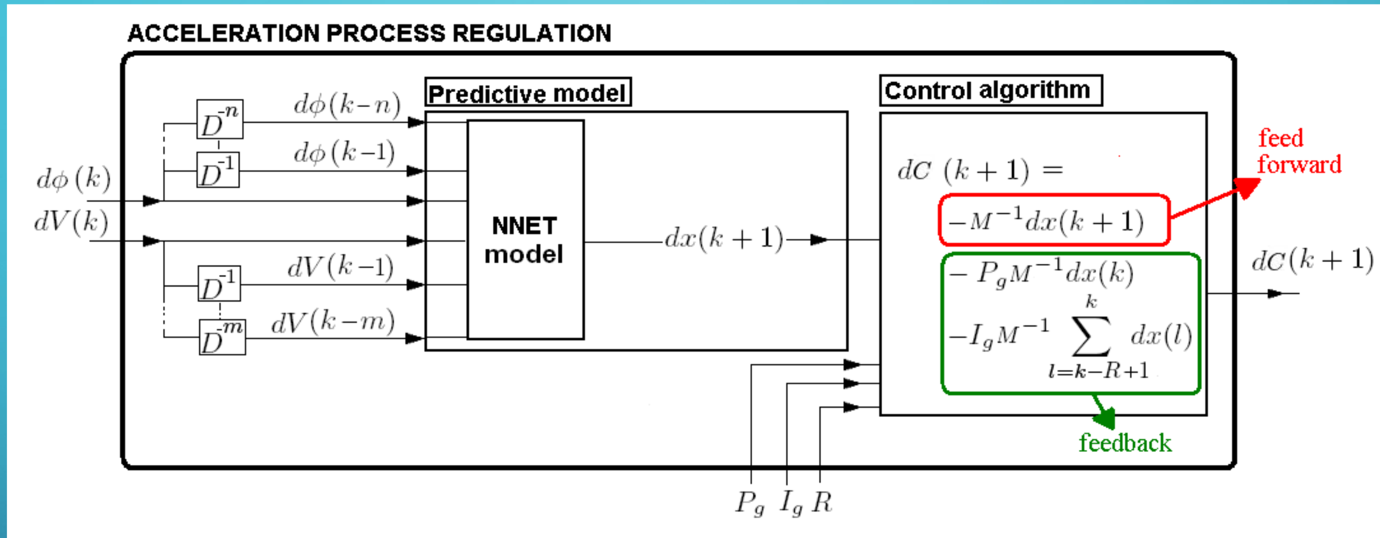
*Recurrent Neural Network - Long Short Term Memory type

AND IN A FEW MINUTES

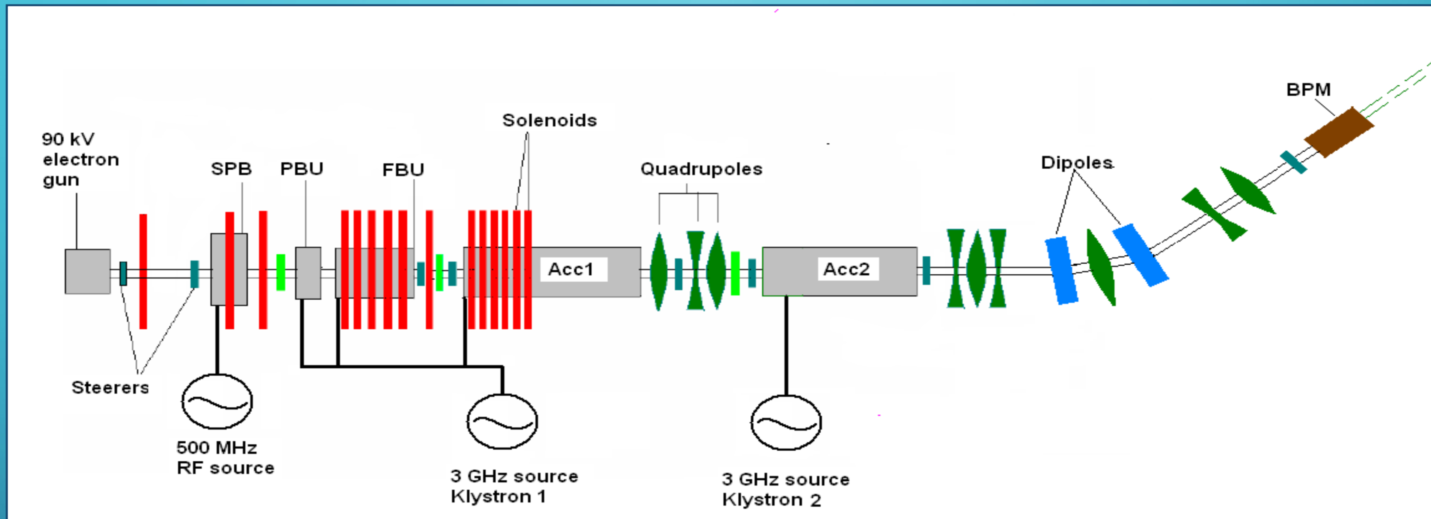
- You will hear about “Operational Results of the LHC Collimator Alignment using Machine Learning” from Gabriella Azzopardi (University of Malta and CERN).

MINIMIZING HIGH-FREQUENCY JITTER

- In order to compensate for the PID algorithm deficiencies, we wanted to build a system that
  - Acted in a feed forward way, for correction of high-frequency jitter
  - Increased the bandwidth in order to avoid re-tuning when conditions change.
- We recorded data from the machine in order to train a neural network to predict a future deviation based on past records.
- We complemented the system with an optional PI algorithm to further decrease remaining deviations.

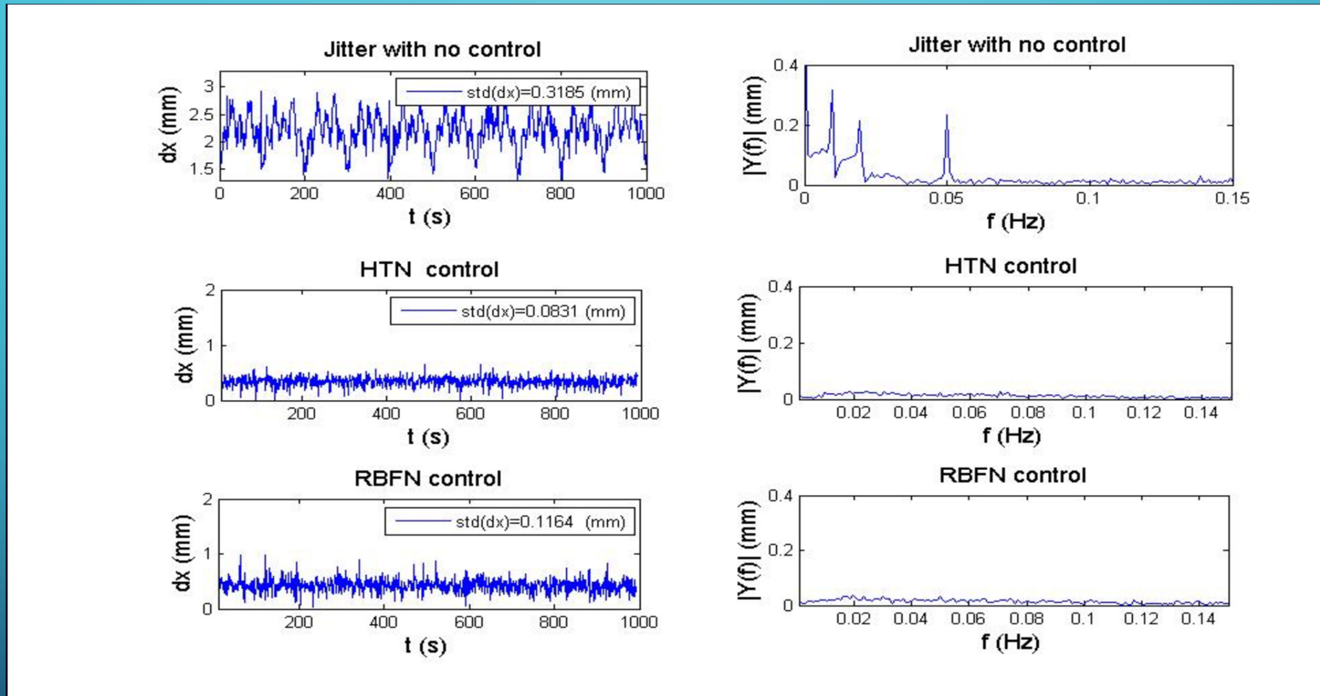


- **Predictive model (left block):** The Neural Network (NNET) receives lagged values of the perturbed klystron phase and voltage. It gives a prediction of the next pulse position deviation *dx(k+1)* used to compute the feed forward correction.
- **Control algorithm (right block):** The algorithm is composed of a feed forward (first term) augmented by PI control terms (second and third terms) to compute the correction to apply *dC(k+1)* .



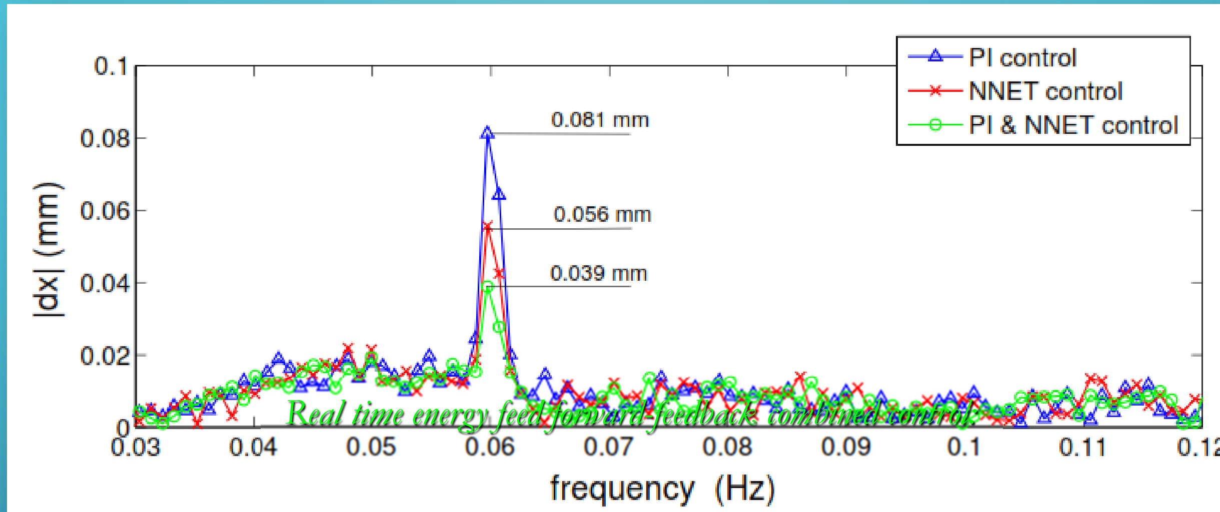
- ACC1 and ACC2 provide 100 MeV beam @ 1-10Hz.
- BPM resolution ~50µm , white noise level ~0.11 mm rms
- Jitter are induced in klystron 1 phase and voltage and corrected using klystron 2 voltage
- Slow actuator response limits the experiment to max. ~0.075 Hz

REAL TIME ENERGY CONTROL



Both the hyperbolic tangent network (HTN) and radial basis function network (RBFN) received 7 lagged values of V_1 and 5 lagged values of ϕ_1. The HTN and RBFN had 7 and 76 hidden neurons, respectively.

Real Time energy feed-forward feedback control.



- The PI controller was tuned for a 0.4 Hz perturbation.
- The NNet was trained to correct the same 0.4 Hz perturbation .
- A shift in frequency to 0.6 Hz shows that the NNet operates better than the PI, and that the combined controlled provides further decrease of the perturbation amplitude.

E. Meier, M. Morgan, S.G. Biedron, G. LeBlanc, J. Wu, 2009, "Development of a Combined Feed Forward- Feedback System for an Electron Linac," Nuclear Instruments and Methods in Physics Research Section A: Accelerators, Spectrometers, Detectors and Associated Equipment 609, 79-88.

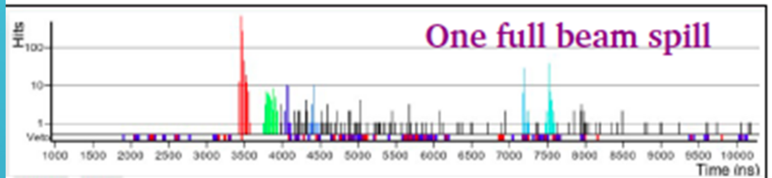
AND NOT FORGETTING OTHER FIELDS

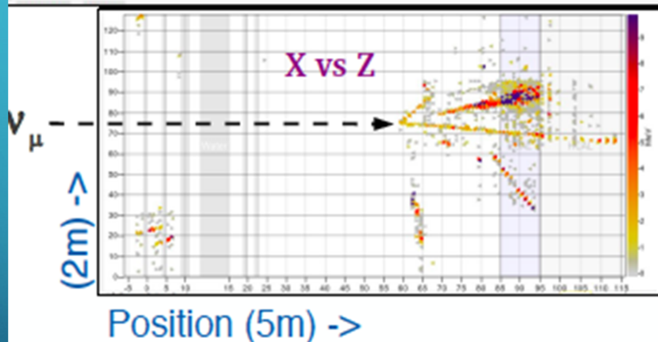
- Employing these algorithms has demonstrably sped up calculations (e.g. one million times for analysis of strong lenses) and produced clear cost-savings (30% increase in effective detector volume for neutrino flavor tagging with neural networks). These faster algorithms enable accelerated science, and in some cases they lead to paradigm shifts: in situations where it once required one day for a human to analyze a single object.
- Also see a recent talk/work by Gabriel Perdue (FNAL) -> next chart

- Y. D. Hezaveh, L. P. Levasseur, and P. J. Marshall, "Fast automated analysis of strong gravitational lenses with convolutional neural networks," Nature, vol. 548, pp. 555–557, Aug. 2017; P. Adamson et al., "Constraints on oscillation parameters from ne appearance and nμ disappearance in nova," Phys. Rev. Lett., vol. 118, p. 231801, Jun 2017. [Online]. Available: https://link.aps.org/doi/10.1103/PhysRevLett. 118.231801; M. A. Acero et al., "New constraints on oscillation parameters from ne appearance and nμ disappearance in the nova experiment," Phys. Rev. D, vol. 98, p. 032012, Aug 2018. [Online]. Available: https://link.aps.org/doi/10.1103/PhysRevD.98.032012

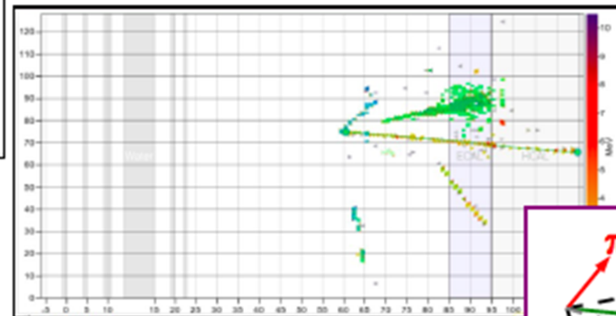
Why deep learning is interesting for neutrinos in one slide...

Because, just *look* at them!

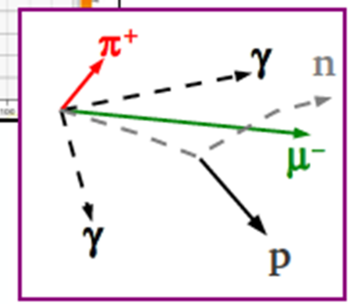




Event reconstruction



My guess, just for fun



Modern neutrino detectors are imaging detectors. Domain experts can discern an enormous amount of information visually. But feature engineering is hard.

Fermilab

Courtesy Jim Amundson

USERS OF ACCELERATORS OUTSIDE OF HEP

- LANL LDRD -> LDRD - Real-time Adaptive Acceleration of Dynamic Experimental Science.
- D. J. Walters, A. Biswas, E. C. Lawrence, D. C. Francom, D. J. Luscher, Fredenburg, D. A., K. R. Moran, C. M. Sweeney, R. L. Sandberg, J. P. Ahrens and C. A. Bolme. Bayesian calibration of strength parameters using hydrocode simulations of symmetric impact shock experiments of Al-5083. Journal of Applied Physics. 124 (20): 205105. (LA-UR-18-20884 DOI: 10.1063/1.5051442)
- Orban, D. T., D. Keefe, A. Biswas, J. P. Ahrens, and D. H. Rogers. Drag and Track: A Direct Manipulation Interface for Contextualizing Data Instances within a Continuous Parameter Space: Application to Shock Physics. Presented at IEEE Vis. (Berlin, Germany, 2018-10-21 - 2018-10-26). (LA-UR-18-22844)
- Biswas, A., J. P. Ahrens, and E. C. Lawrence. High-Dimensional Data Analysis and Visualization Using High Fidelity Emulators with Uncertainty. Presented at IEEE Visualization (Berlin, Germany, 2018-03-31 - 2018-03-31). (LA-UR-18-22810)
- Orban, D., D. Banesh, C. Tauxe, C. M. Biwer, A. Biswas, R. Saavedra, C. Sweeney, R. L. Sandberg, C. A. Bolme, J. Ahrens, and D. Rogers. “Continuous workflow and exploration of disparate data types using Cinema:Bandit: A toolset for beamline science demonstrated on XFEL shock physics experiments.” LA-UR-19-22551 (2019). In journal review.
- Biwer, C. M., S. C. Vogel, M. M. McKerns, and J. P. Ahrens. “Spotlight: Automation of Rietveld analyses using an ensemble of local optimizers.” LA-UR-18-30288 (2018).
- Vogel, S. C., C. M. Biwer, D. H. Rogers, J. P. Ahrens, R. E. Hackenberg, D. Onken, and J. Zhang. “Interactive visualization of multi-data-set Rietveld analyses using Cinema: Debye-Scherrer.” Journal of Applied Crystallography 51, no. 3 (2018).

OPTICS/IMAGING, ONE EXAMPLE

- **Advanced Optical Imaging for Extreme Environments**
- **https://ieeeaccess.ieee.org/special-sections/advanced-optical-imaging-for-extreme-environments/**
- **Submission Deadline:** 1 July 2019
- IEEE *Access* invites manuscript submissions in the area of Advanced Optical Imaging for Extreme Environments.
- Modern day optical systems are capable of doing more than ever before with less size, weight, and power. With the rare exception, however, these optical systems and optical processing methods adhere to age-old architectures that drive practical solutions towards unsustainable complexity under ever-increasing performance requirements. The performances of optical imaging systems will be largely jeopardized by various challenging conditions in unconstrained and extreme environments, e.g., rainy, foggy, snowy, and low illumination environments. Researchers need to reinvent optical devices, systems, architectures, and methods for extreme optical imaging. On the other hand, artificial intelligence has become a topic of increasing interest for researchers. It is foreseeable that artificial intelligence will be the main solution of the next generation of extreme optical imaging. To this end, the goal of this Special Section in IEEE Access is to provide a platform to share up-to-date scientific achievements in this field.
- Low Light Imaging and Processing, Underwater Image Processing, Imaging Using Extreme Big Data, Infrared Imaging and Processing, Extreme Physics-based Optical Imaging, Modeling Vignetting Processing, Computational Optical Imaging, Imaging in Harsh or Unconventional Environments, Imaging at Extreme Size Scales, Big Multimedia for Extreme Optical Imaging, Applications of Extreme Imaging Systems, Extreme Optical Imaging Sensors, Optical Imaging for Surgical Robotic Networks Intelligence Optical Imaging and Processing, Mixed Reality/Augmented Reality for Extreme Imaging

BACK TO THE HORSE – WE CAN'T ARCHITECT A HORSE
SYSTEMS ENGINEERING IS PART OF THE EQUATION
Building In Intelligence And Data Science From Day 1

- We as a community do not apply systems engineering principles to particle accelerators.
- When planning a new or upgrading an old-ish machine, we need to remind ourselves that we need to come out of the 1930s when architecting the machines.
- If we want to use data science tools, then we need to architect this goal into the system (or system upgrades) – real-time data logging, local computing (e.g. GPUs, FPGAs), application-specific integrated circuits, co-location to a powerful cluster or HPC, better diagnostics, bettter electronics, etc.
- From our experience, for instance, powerful and smart controls tools cannot be mounted onto systems not architected to handle such data science applications!

If we want to have data science as a priority, the facets of data science must be architected into our system or sub-system.

RESEARCH FOR US TO DO

- ML can look for glitches in our software (simulation software as well as controls software). ML, for instance, can learn where the glitches are, find vulnerabilities, and even help detect cyber breaches (control and data systems). *Think of this as having a few extra (thousand, million, etc.) friends helping manually verify the software and protect your accelerator.*
- Use of specialized computing hardware — such as FPGAs, application-specific integrated circuits, systems-on-a chip are in wider use by our cousins in HEP and are natural stepping stones toward dedicated AI hardware – if we can implement, test and continue to develop on many accelerator systems.
- In the case of the quest for compact, accelerators, the more data we have on a "prototype" the better and cheaper we can make the next versions to be produced and sold. Intelligent methods will be important here.
- We need to generate new intelligent techniques and algorithms specifically to address the underlying physics in an accelerator and peripheral systems (e.g. lasers).
- We have some of the most interesting data sets in the world generated on our machines and by our users. Just in the acquired data thus far, we can be exploring accelerator-specific data science techniques.
- We need to be aware that controls using traditional techniques and/or more intelligent techniques could be improved through better use of data science.

Thanks to Jim Amundson, Josh Stein, John Cary, Richard Farnsworth, Steve Lidia, John Petillo, and Massimo Dal Forno for discussions.

ALSO – LOOKING OVER THE FENCE

- We need to look over the fence at groups such as HEP for guidance with large-scale data acquisition.
- Not all improvements need to be focused around AI. There are many controls algorithms, for instance, that can be adapted from other fields first. The most challenging problems should be left to the most “intelligent” approaches. (See list of journals in the back-up charts).
- We need to be smart about using intelligence (See background from the IEEE Standards society working to ethical design practices.)

CONCLUSIONS

- To effectively apply data science to the accelerators, you must have knowledge of the system and physics, engineering, materials, chemistry, etc. behind it.
- Need to choose the right algorithm to tell you about the system, not just about the data interpretation you already know.
- Need to find the right data set for the question(s) you have. This includes the diagnostic (how you got the data).
- We need to realize that we ourselves have to improve our own methods or adapt to a "new job" (e.g. we are now taking something we examined with genetic algorithms and now using a deep belief network algorithm to formulate our control.)
- We need to convince the managers as well as the funding agencies that data science is a low-hanging fruit in particle accelerators.
- And I believe that accelerator people that already do so much cross-disciplinary can really make a huge impact here with data science. (We just have to block out and go around the people that reward the one trick ponies.)
- Lots of work yet to do.

The only working model of a universe is a universe.