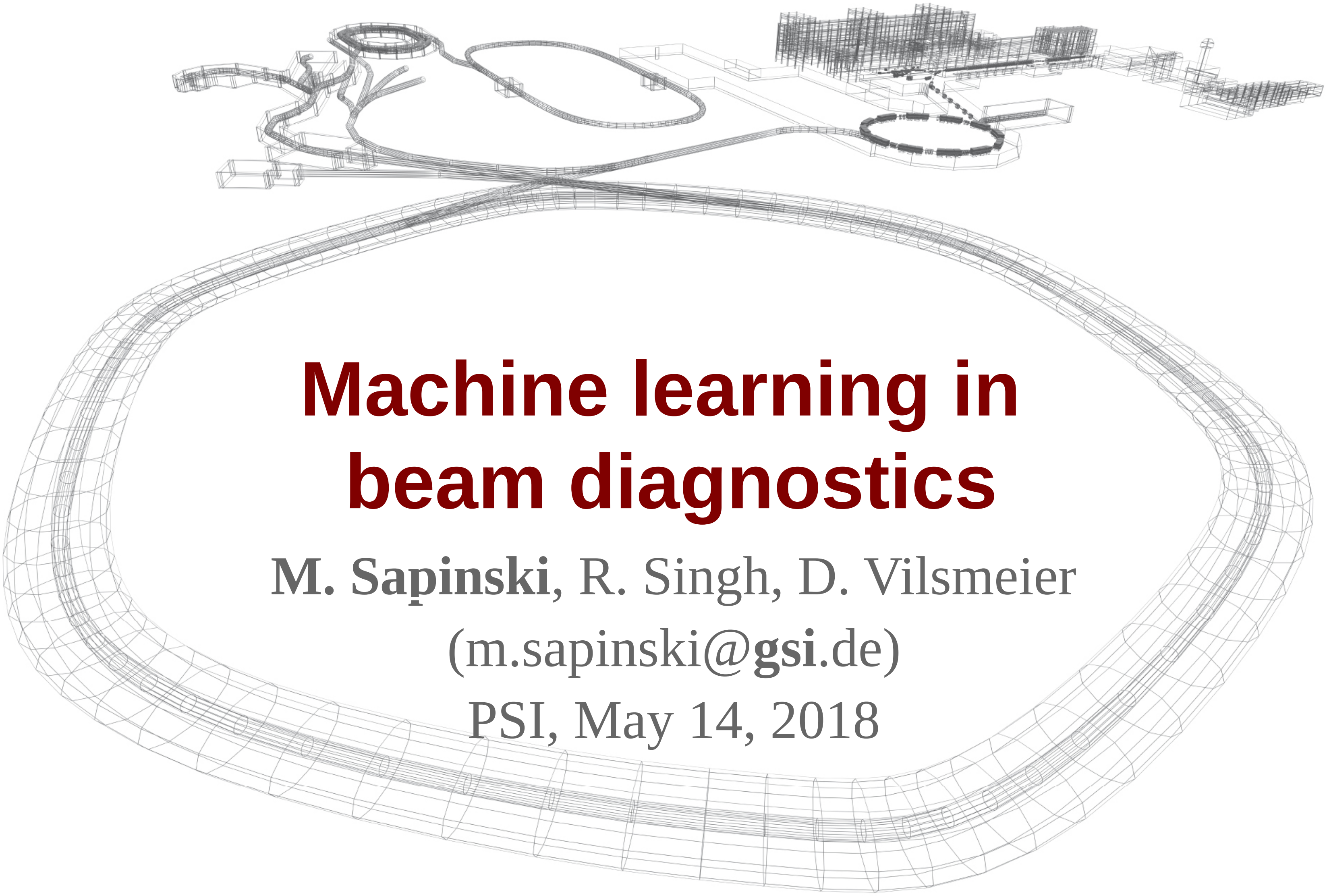


Machine learning in beam diagnostics

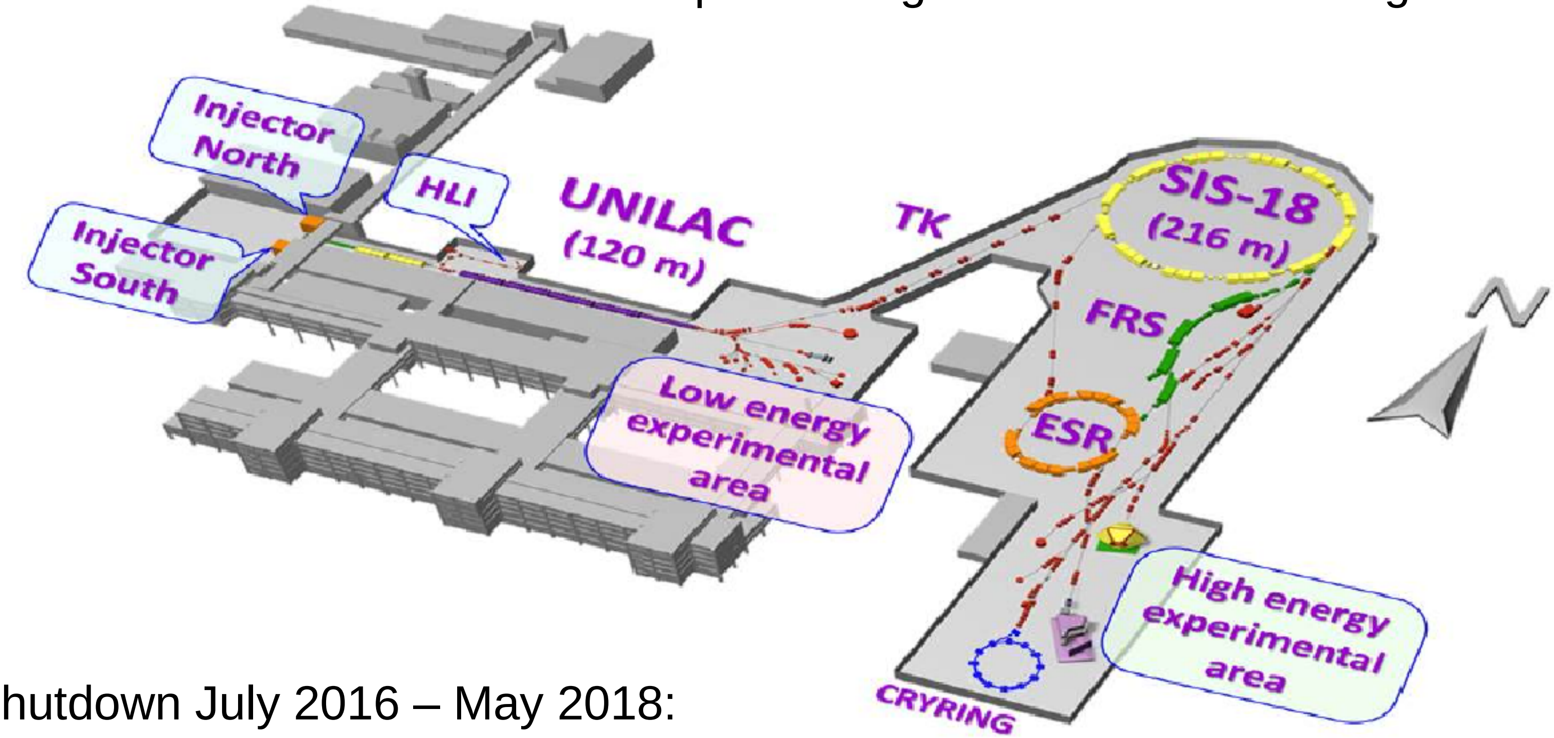
M. Sapinski, R. Singh, D. Vilsmeier
(m.sapinski@**gsi**.de)

PSI, May 14, 2018

GSI and FAIR

GSI status

https://www.gsi.de/work/beschleunigerbetrieb.htm



1. shutdown July 2016 – May 2018:
   - new control system (LSA)
   - prepare connection of SIS18 to SIS100
   - prepare SIS18 to high-intensity run
2. beam commissioning starts in 2 weeks

Accelerator beam time starts in

14	9	10	28
days	hours	min	sec

Outline

- Introduction: what is Machine Learning?
- Some famous examples.
- Artificial Neural Networks.
- Theoretical background.
- Example 1: identification of quench-provoking loss patterns at LHC.
- Example 2: correction to measured beam profile distortion in Ionization Profile Monitor.
- Remark: IPM for XFEL?
- Conclusions.

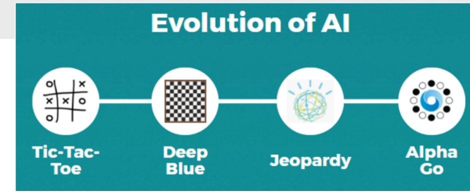
Remarks and Disclaimer

- Beam Diagnostics takes care of beam parameters measurements, for example: beam position, beam current, longitudinal and transverse profile, beam loss, tune, chromaticity, etc.
- Machine Learning techniques are also used in other aspects of accelerators, mainly control systems, machine tuning – not discussed here.
- Keep in mind that I am enthusiast, but not trained Machine Learning professional.

What is Machine Learning?

- Algorithms which can learn and make predictions on data, without explicit programming.
- The term by Arthur Samuel (IBM) in 1959.
- Machine learning is closely related to computational statistics and to mathematical optimization.
- Data mining is a sub-field of Machine Learning known as unsupervised learning.
- Expert systems – are made of digitized/encoded expert knowledge. They are not Machine Learning algorithms. Still useful is there is little data available for training. Mixed systems are also available.

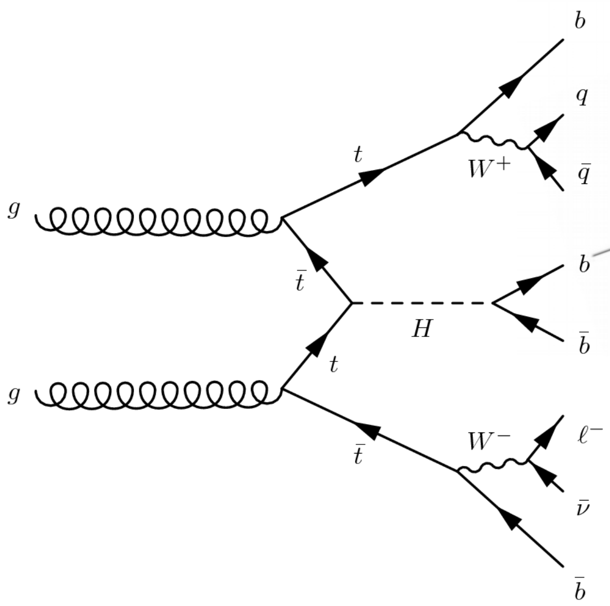
Examples of ML-based projects (I)

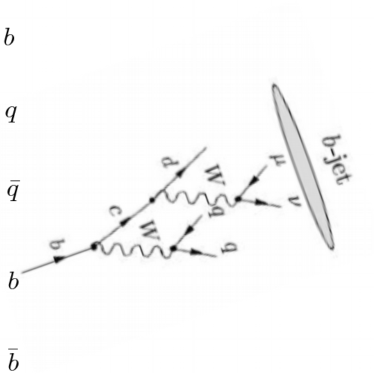


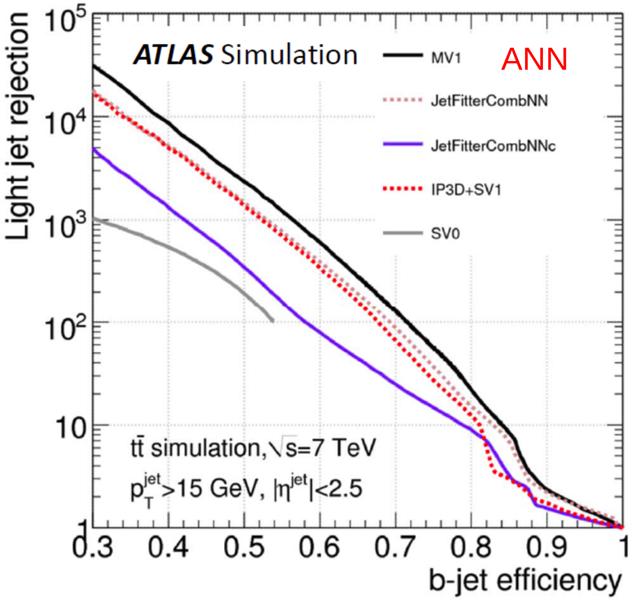
- AlphaGo :
  - Go is difficult for algorithms because of number of configurations (>2x10^{170},chess only ~5x10^{52}), atoms in the Universe ~ 10^{80}.
  - The program uses Artificial Neural Network for learning and Monte Carlo Tree Search for decide about next move.
  - 1 year learning time, 183 MWh energy, excessive data sample – not the way human learns, but:
    - AlphaGo won against the highest-qualified humans.
    - It has exhibited creative skills making moves seldom done by humans.

Examples of ML-based projects (II)

- Neural Networks are used in physics analyses since ~1988.
- They were for instance used to reject background in Higgs boson search – but published analysis does not use ML.
- b-tagging:





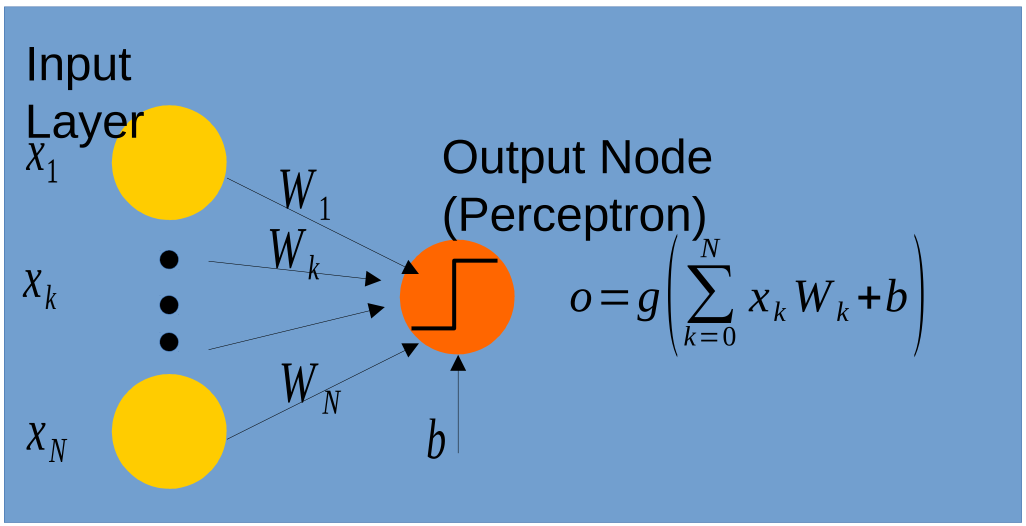


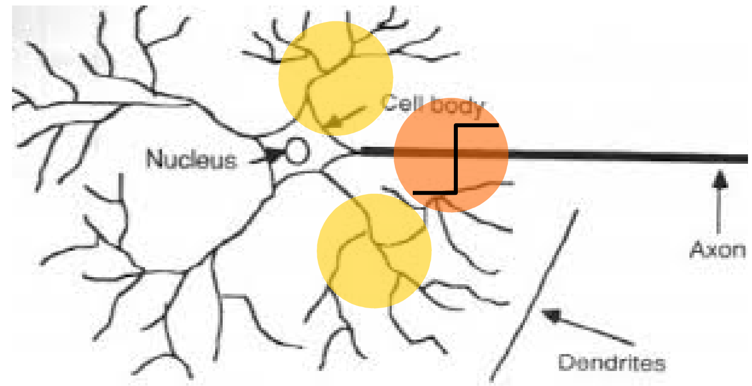
the scope of this presentation is:

- show examples how Machine Learning techniques, mainly artificial neural networks (ANN), can be useful to solve everyday problems of accelerator physicist in domain of beam instrumentation.

Artificial Neural Network

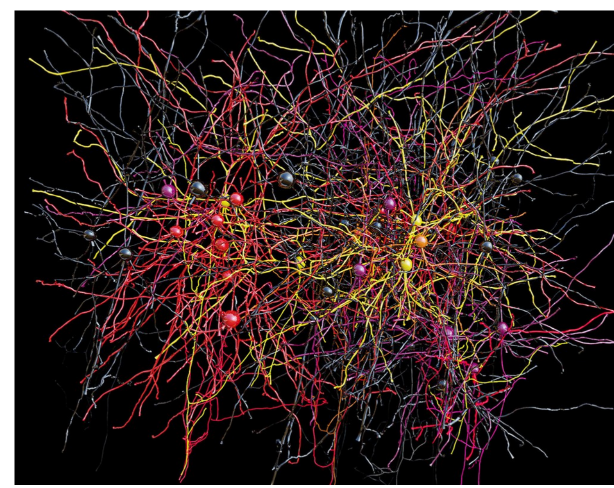
- Biologically inspired → Brain cells -> neurons, computation via connections and thus Networks
- The basic node of ANNs is “Perceptron”





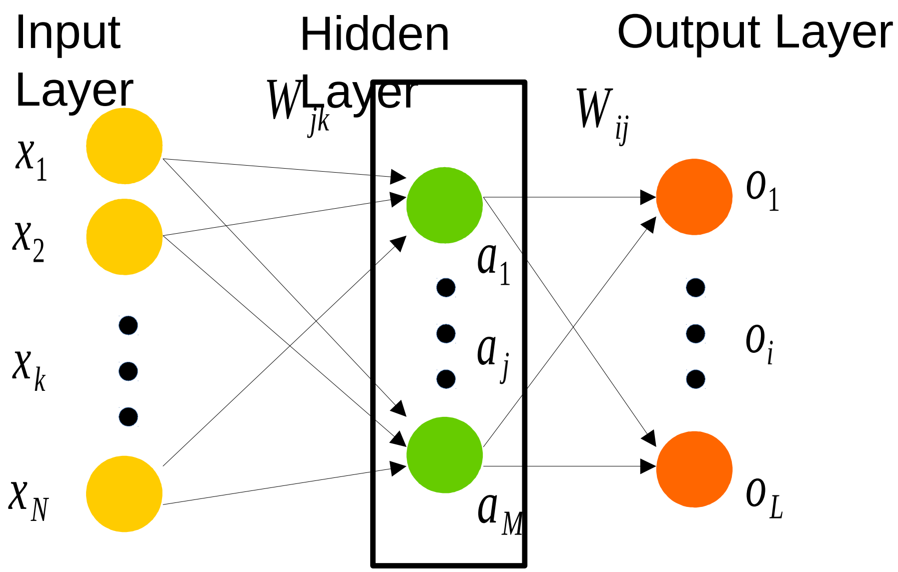
Perceptron parameters:

- Weights from the inputs (X) and bias (b)
- g is the activation function, a step-like function with a threshold



[https://www.wired.com/2016/03/took-neuroscientists-ten-years-map-tiny-slice-brain]

Hidden layers



Multi-layer Perceptron

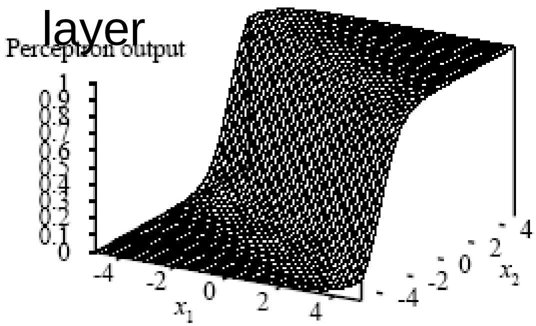
- Each hidden layer and output layer node is a perceptron

$$o_i = g\left(\sum_{j=0}^{M} W_{ij}\left(g\left(\sum_{k=0}^{N} x_k W_{jk} + b_j\right)\right) + b_i\right)$$

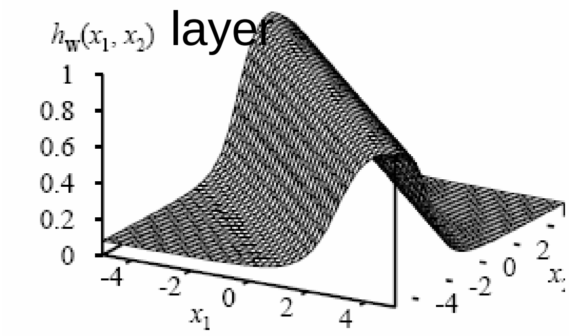
Adding “hidden” layer(s) allow non-linear target functions to be represented

Multi-layer perceptron (MLP)

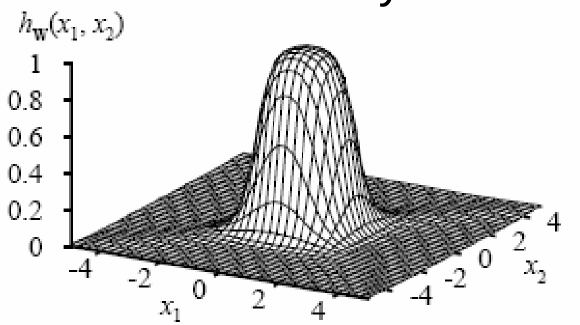
Perceptron: No hidden layer



One hidden layer



Two hidden layers



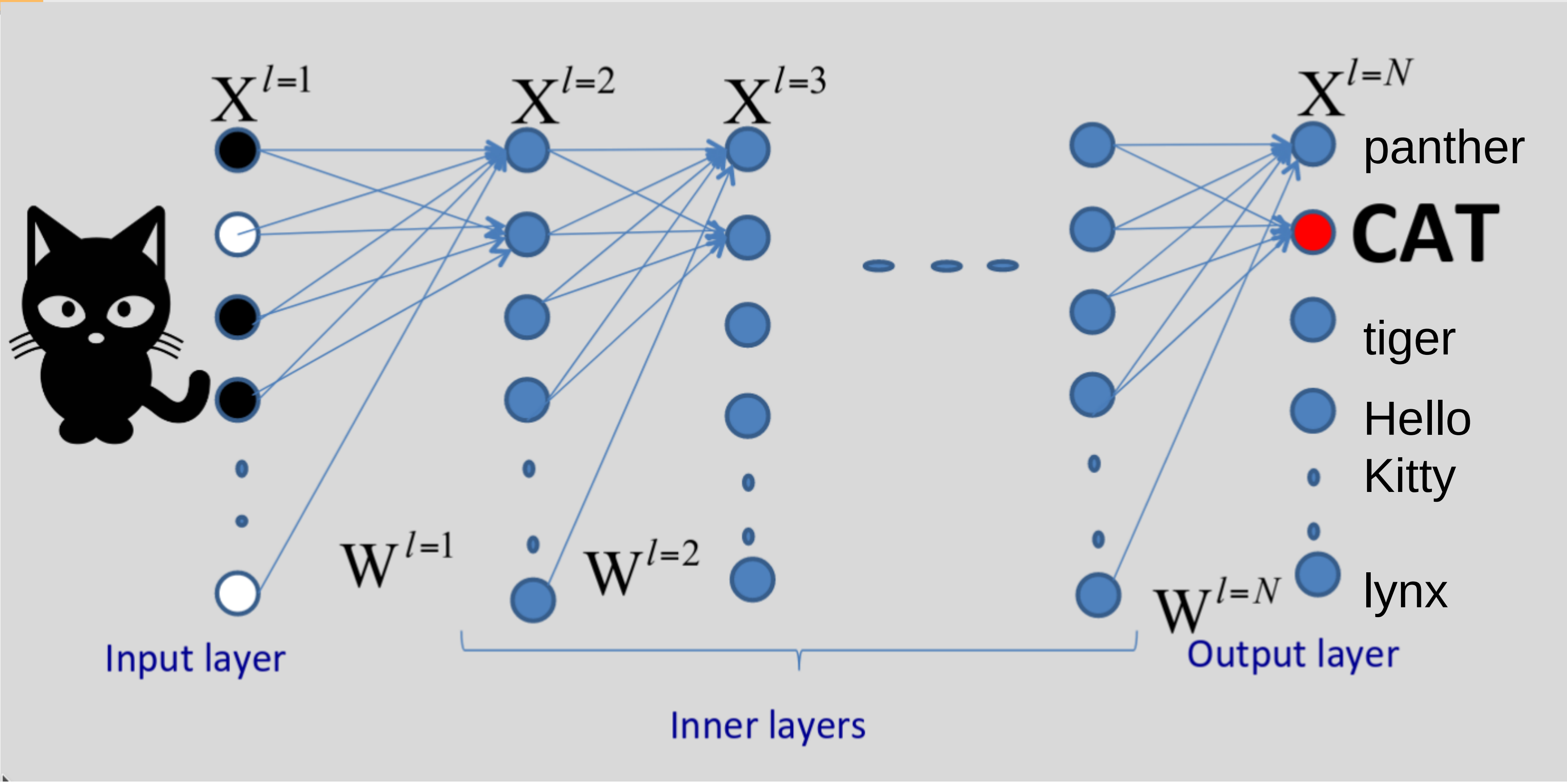
- Carla P Gomes, Lecture Notes CS 4700: Foundations of Artificial Intelligence

- **Universal approximation theorem:**
- Every bounded continuous “target” function can be approximated with arbitrarily small error, by network with single hidden layer [Cybenko 1989; Hornik et al. 1989]

If we have any unknown function, $y=f(x)$,it can be approximated by:

$$o_i = g\left(\sum_{j=0}^{M} W_{ij}\left(g\left(\sum_{k=0}^{N} x_k W_{jk} + b_j\right)\right) + b_i\right)$$

Multi-layer perceptron (MLP)



How to design MLP topology for a given problem?
How to find the weights? (train network)

MLP Network design (feed-forward)

From: https://www.solver.com/training-artificial-neural-network-intro

- *There is no best answer to the layout of the network for any particular application. There are general rules:*
  - As the complexity between input and output increases, the number of the perceptrons in the hidden layer should also increase.
  - If the process being modeled is separable into multiple stages, then additional hidden layer(s) may be required. Otherwise additional layers may simply enable memorization of the training set, and not a general solution effective with other data.
  - The amount of training data sets an upper bound for the number of perceptrons in the hidden layer(s).
    If you use too many perceptrons the training set will be memorized.
  - ->generalization of the data will not occur, making the network useless on new data sets.

MLP Network training (I)

- Some algorithms known since 40's
  (Gauss Newton or Levenberg-Marquardt).
- Backpropagation with Gradient Descent developed in 70's
  – speeds up in ANN training – it triggered a wave of interest in ANN applications – still most popular.

MLP Network training (II)

- How it works:
  - Activation function g must be differentiable, eg. sigmoid or tanh.
  - Initial weights chosen randomly.

$$o_i = g\left(\underbrace{\sum_{j=0}^{M} W_{ij}\left(g\left(\sum_{k=0}^{N} x_k W_{jk} + b_j\right)\right) + b_i}_{inp_i}\right)$$

  - For training record (or a batch of records) a cost function (or loss or error) is calculated, for instance mean squared error:
  - (y-desired output, o-actual output)

$$\boxed{E = \sum_{i=0}^{L} \left(y_i - o_i\right)^2}$$

  - The cost function gradient is calculated for each layer:

$$\boxed{\frac{\delta E}{\delta W_{ij}^{1}} = a_j Err_i g'\left(inp_i\right)}$$

$$\boxed{\frac{\delta E}{\delta W_{jk}^{2}} = x_k g'\left(inp_j\right) \sum_{j=0}^{M} W_{ij} Err_i g'\left(inp_i\right)}$$

  - New weights are calculated:
  - Repeat for new record (but you can use the same record later again)

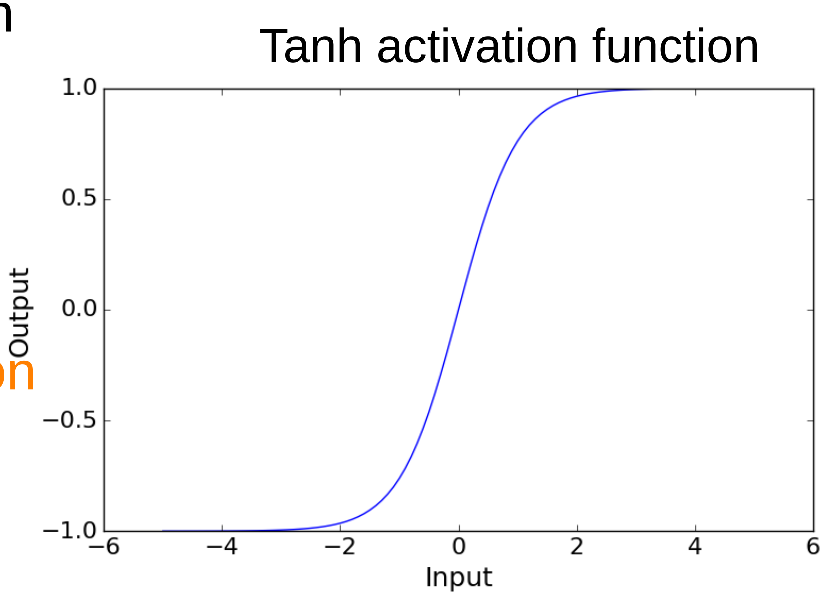
$$\boxed{W\left(t+1\right) = W\left(t\right) + \alpha \frac{\delta E}{\delta W}}$$

α-learning rate

Conditioning inputs and initial weights

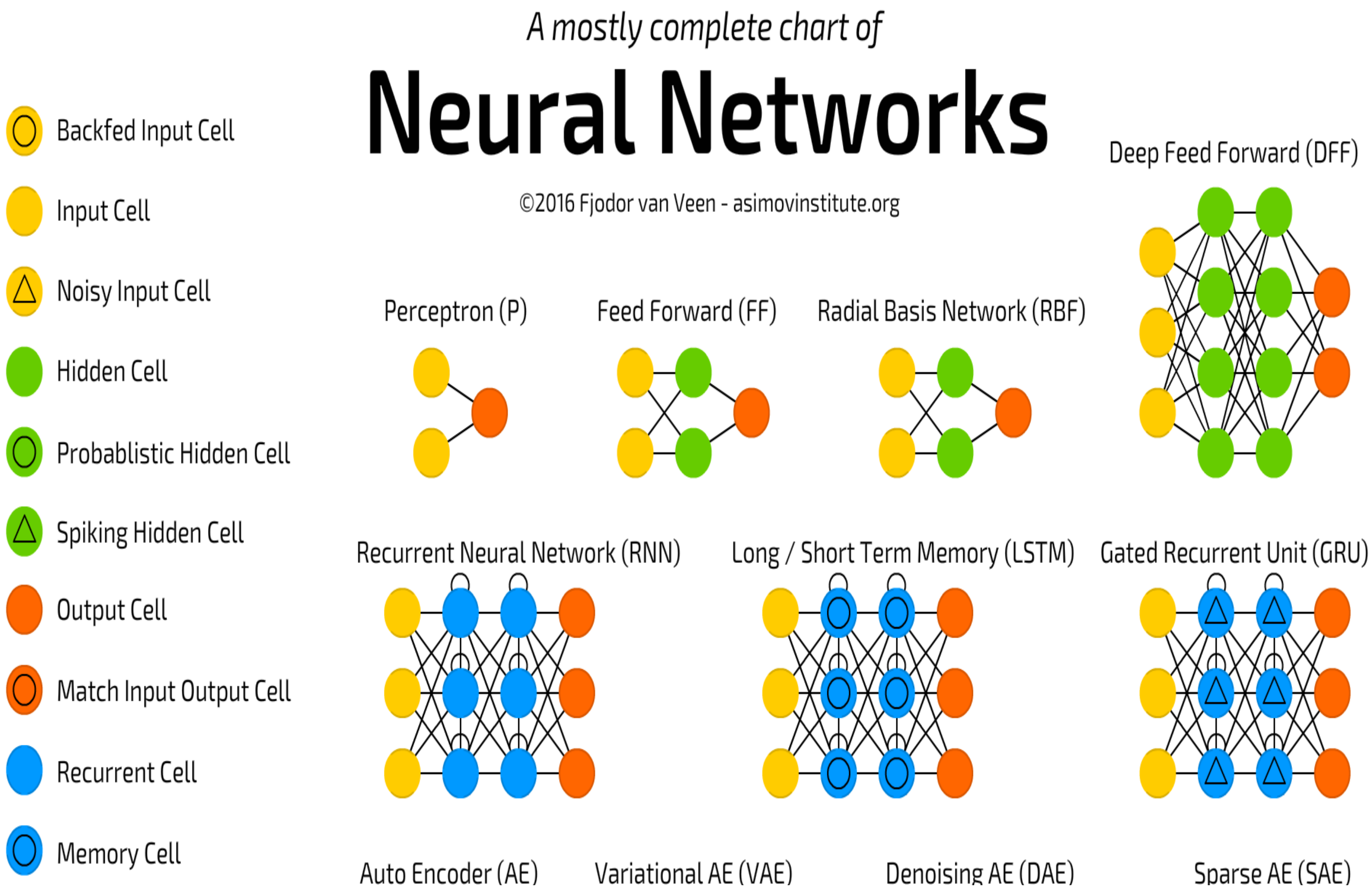
- Weights initialization: Generate random initial weights [-1,1] and divide each of by the square root of the number of units in the larger layer.

- Inputs and targets to be normalized according to the used activation function (tanh: -1..1, sigmoid: 0...1) , else some perceptrons will remain saturated (difficulty in learning).



- Rules of thumb: Start with two hidden layers with number of hidden units equal to (Input_num + Target_num)/2, avoid overfitting by regularization.
- If simple MLP is not good enough for the application, look further into literature!

Neural network Zoo



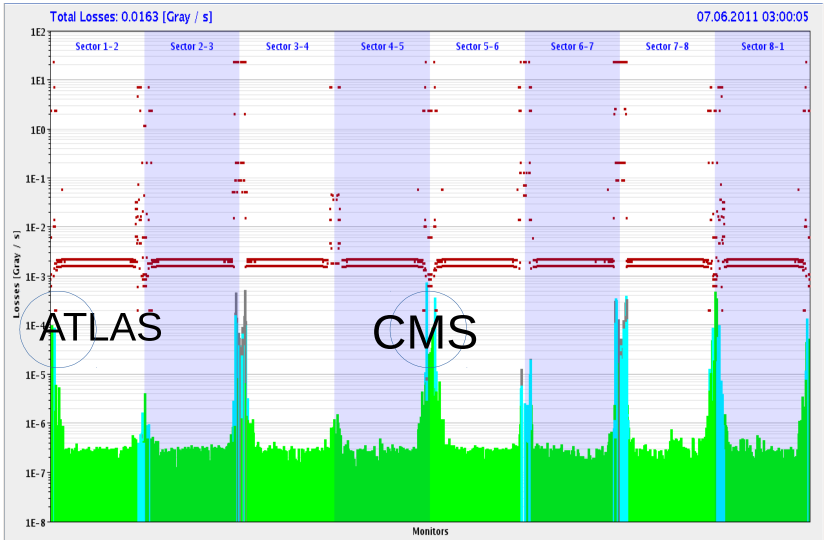
… 20 more

Source: Fjodor Van Veen, Asimov Institute, Utrecht

Example 1:
Pattern recognition in BLM signals

Beam Loss Monitors (BLMs) at LHC:

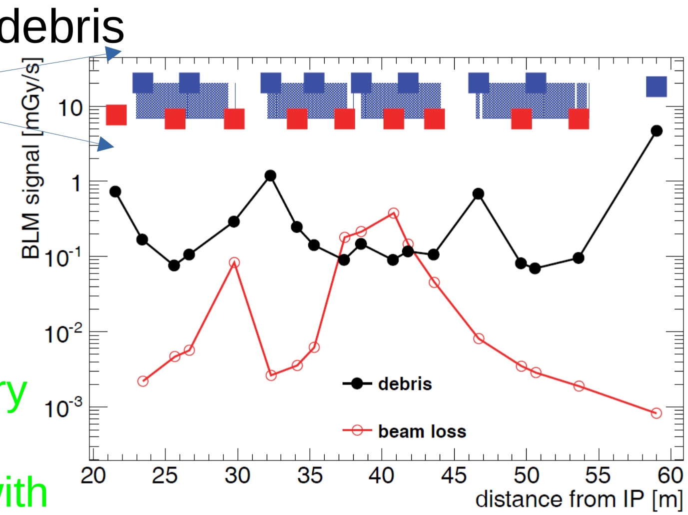
- Most high-power accelerators are equipped with BLM systems.
- LHC beam has energy of about 360 MJ per beam, equivalent to about 300 passenger cars on a motorway.
- Uncontrolled loss of even fraction of such a beam can damage equipment or quench a magnet.
- Therefore about 4000 BLMs are installed around LHC, ready to dump the beam within ~200 µs.



Example 1:
LHC interaction points

- In order to focus the beams in the interaction point (experiment) special high-gradient quadrupoles are installed – called **triplets**.
- Beam-beam collisions produce interesting physics results and debris, which leak to triplets
- Due to that triplet magnet are constantly “heated” to about 30% of quench limit (~3 mW/cc).
- Only small variation of BLM signal corresponds to quench-provoking beam loss. What to do?

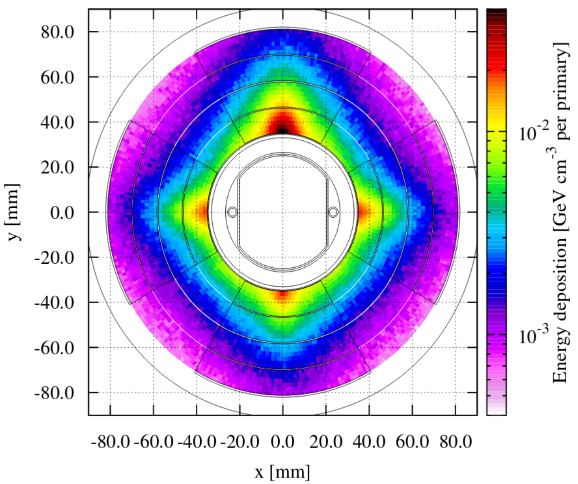
ATLAS /CMS



FLUKA simulations: for debris very good agreement with measurements!

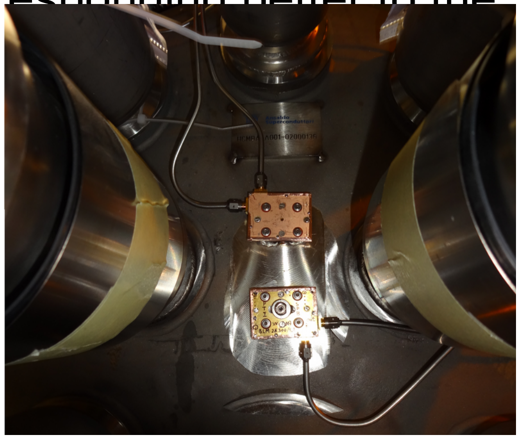
So:

Energy inside magnets shou also be well estimated!



Example 1:
How to recognize beam loss

- First idea: install BLM monitors inside the magnets, close to the coils.
  - Advantage: closer to the coil – measurement corresponding better to the real coil heating
  - Disadvantages: difficult location, small space, no service possible, liquid helium environment, high integrated dose, technical risk due to additional structures inside magnet etc…
  - R&D and test installation done with silicon and diamond detectors, not very promising!



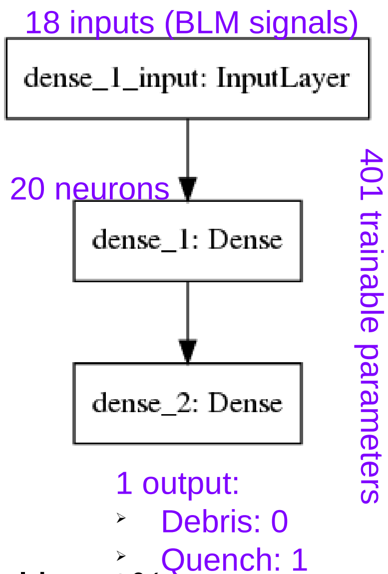
- Test Artificial Neural Network patter recognition capacity!

Example 1:
Some code

- Python
- Google tensorflow library with keras interface:
  >pip install tensorflow
  >pip install keras
- Create ANN:

```
from keras.models import Sequential,Model
from keras.layers import Input, Dense, Activation
import matplotlib.pyplot as plt
import numpy as np

model = Sequential()
model.add(Dense(20, input_dim=18, activation='tanh'))
model.add(Dense(1, init='uniform', activation='sigmoid'))
model.compile(optimizer='rmsprop',
              loss='binary_crossentropy',
              metrics=['accuracy'])
```



- Prepare data:
  - Debris: 100k events with independent random variation of each BLM signal by 10%
  - Loss: 100k events with independent random variation of each BLM signal by 50% MIXED with debris to a quench level.

- Train: model.fit(traindata,trainlabel,nb_epoch=70)
- Run on new data: out_loss=model.predict(testdata)

that's it! 10 – 20 lines of code!

Example 1:
Pattern recognition in BLM signals

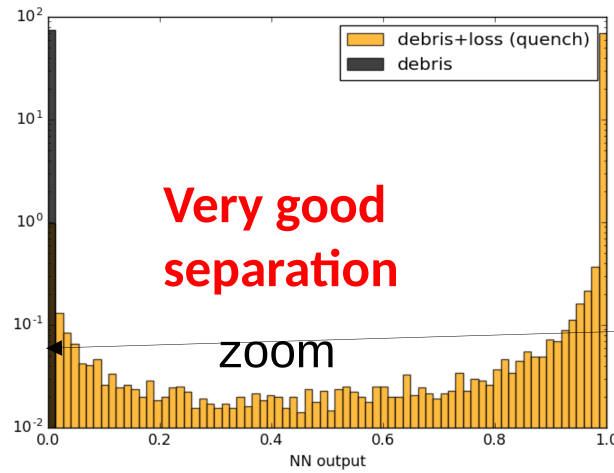
Result:

Overlap: about **0.5%** of quench-provoking losses undetected.

Compare it to standard method, for instance
Mean Square Error between expected debris signal (D_{exp}) and signals at quench.

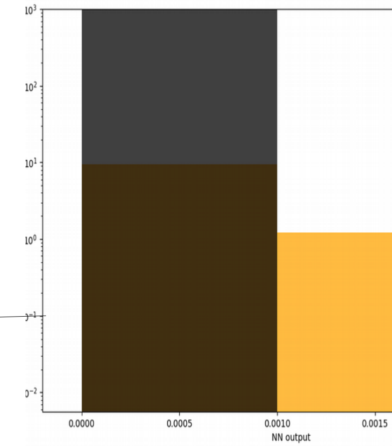
$$MSE = \Sigma(D_{exp,i} - S_i)^2$$

To give more chances to classical signal we limit ourselves to 6 most sensitive BLMs. Otherwise it is the same data.
Overlap: about **2%** of losses undetected.

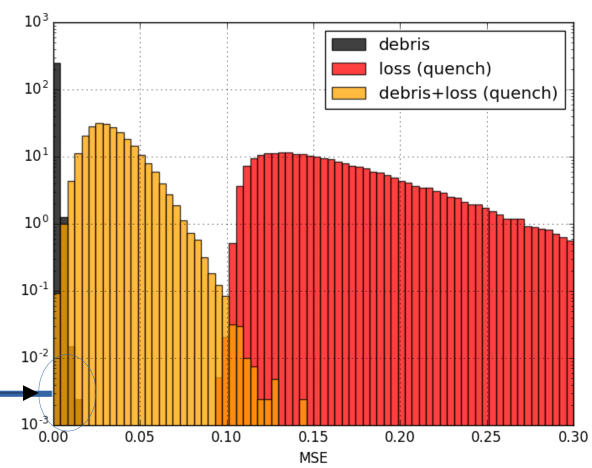


Very good separation

zoom



0.001



Example 1:
Pattern recognition in BLM signals

Lessons learned:

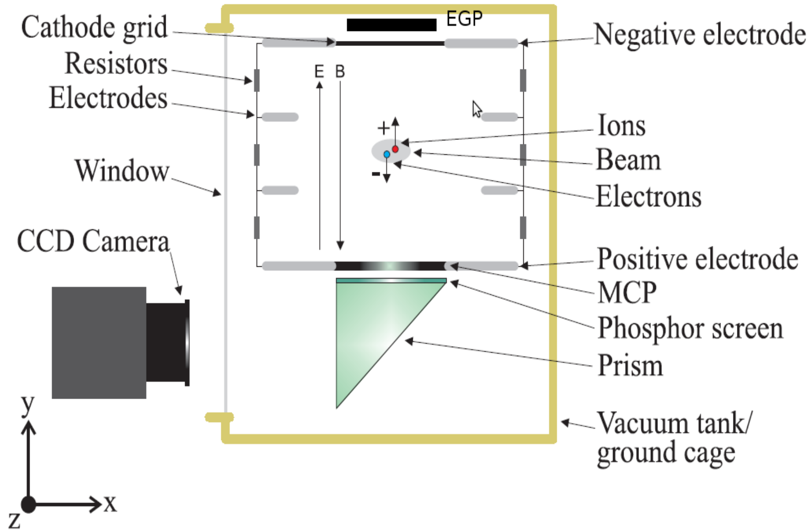
- It took < 1 day to perform this analysis: it is easy!
- Without further optimization the results are better than (simplistic) “classical” approach.

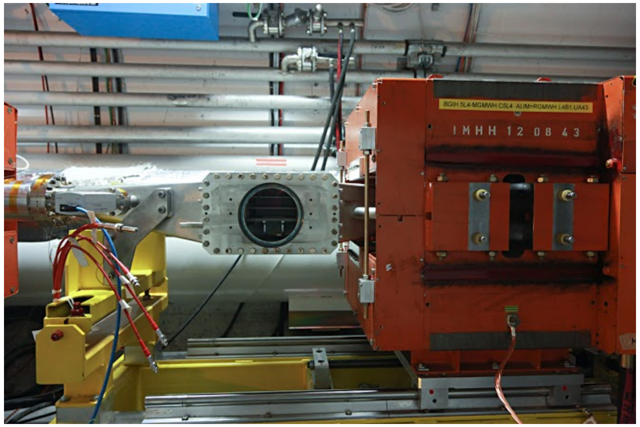
- However this solution was finally not chosen, because people do not like “black boxes”...

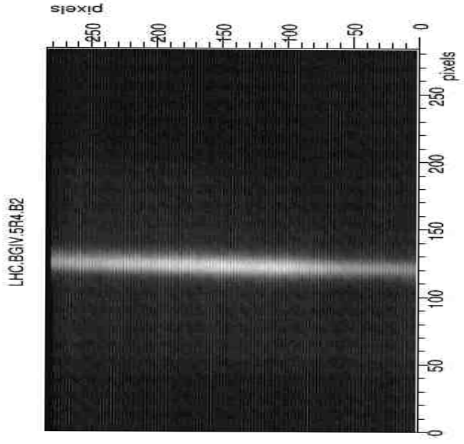
Example 2: Correction of IPM signal distortion due to beam space-charge

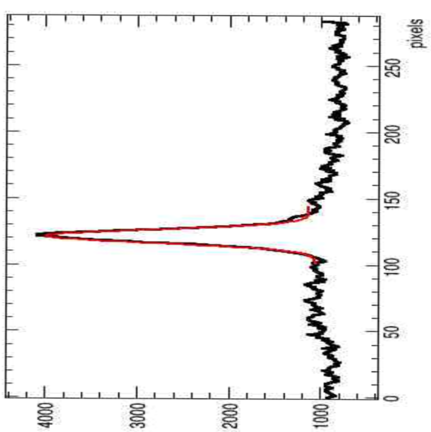
Ionization Profile Monitor (IPM):

- Measures transverse profile of particle beam.
- Rest gas (pressure 10^{-8} mbar) is ionized by the beam.
- Electric field is used to transport electrons/ions to a detector.
- If electrons are used – additional magnetic field is usually applied to confine their movement.



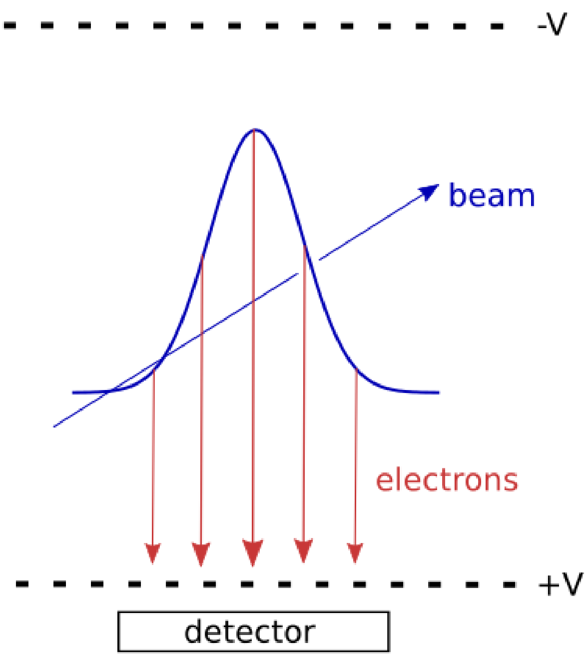




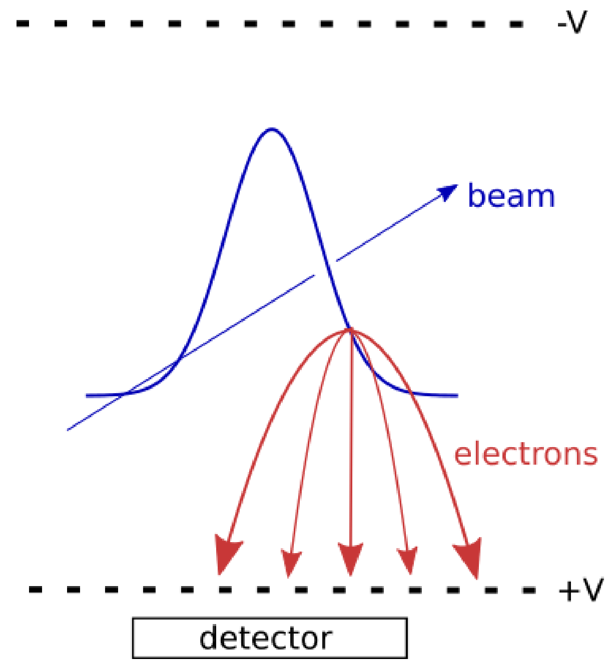


Example 2:
Profile distortion in IPM

- Ideal case
- Particles are moving on straight lines towards the detector



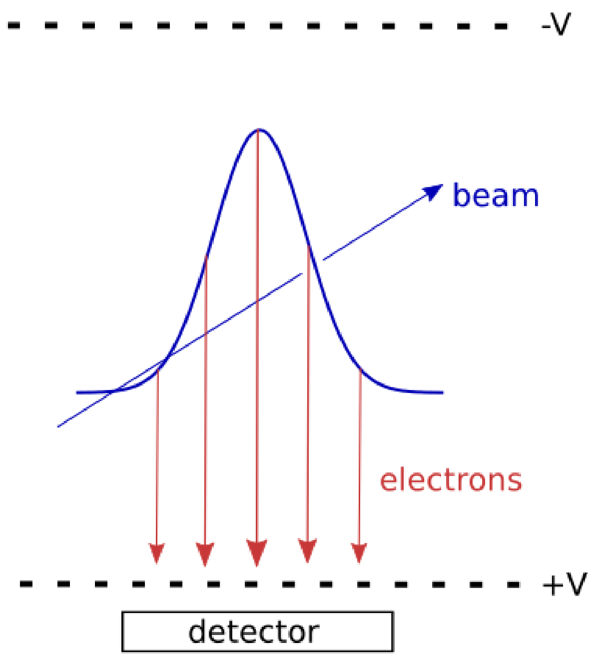
- Real case
- Particle trajectories are influenced by initial momenta and by the interaction with the beam field



… instrumental effects such as camera tilt, optical point-spread-functions, point-spread functions due to optical system and multi-channel plate granularity etc, etc… come on top!

Example 2:
Profile distortion in IPM

- Ideal case
- Particles are moving on straight lines towards the detector



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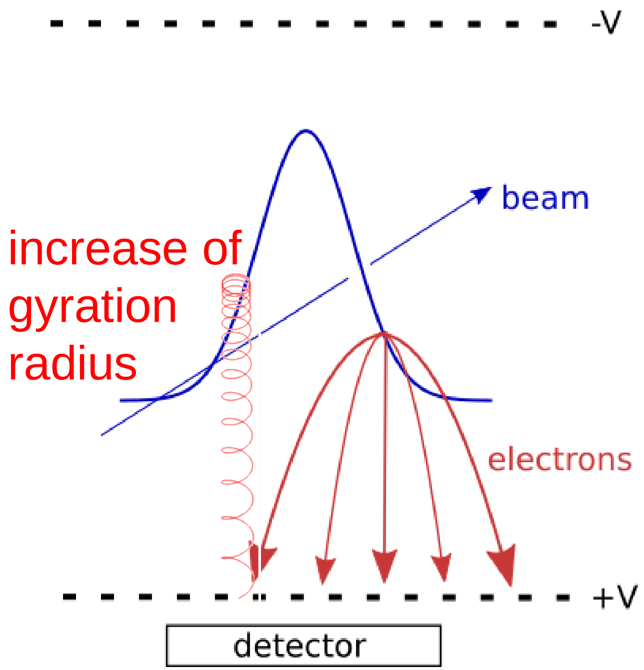
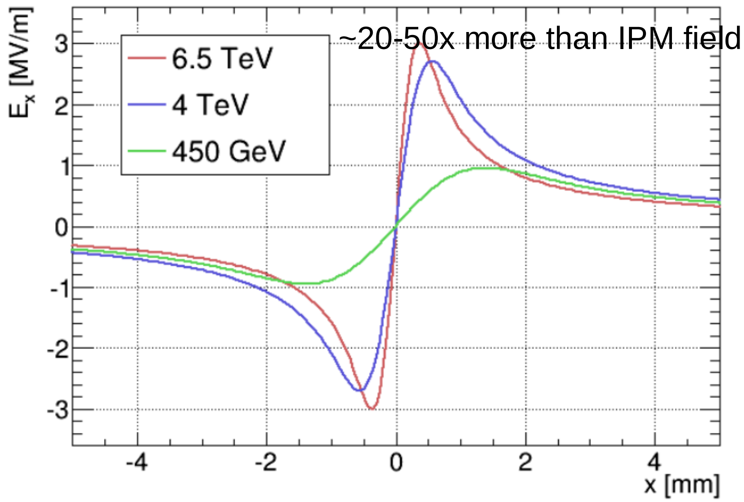
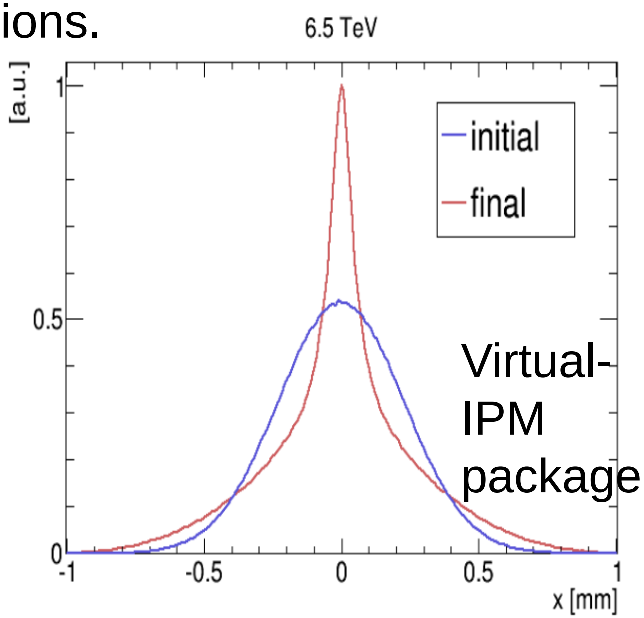


… instrumental effects such as camera tilt, optical point-spread-functions, point-spread functions due to optical system and multi-channel plate granularity etc, etc… come on top!

Example 2:
Profile distortion in IPM - simulation

- Focus on beam field influence.
- Electrons “feel” beam fields (E) and their movement is influenced accordingly resulting in possible displacements.
- This occurs for large beam fields ↔ large charge densities, large beam energies.
- Can be simulated with reasonable assumptions.





Virtual-IPM package

Example 2: IPM profile corrections

- No simple analytical procedure exists.
- Using higher electric and magnetic fields (expensive, sometimes impractical).

- Electrons + electric and magnetic fields: Sieve method (deconvolve with PSF of radius of Gyration) – difficult in practice.

  [Dominik Vilsmeier, Bachelor Thesis, CERN]

- Electric fields only (ions): several calibration/correction attempts.

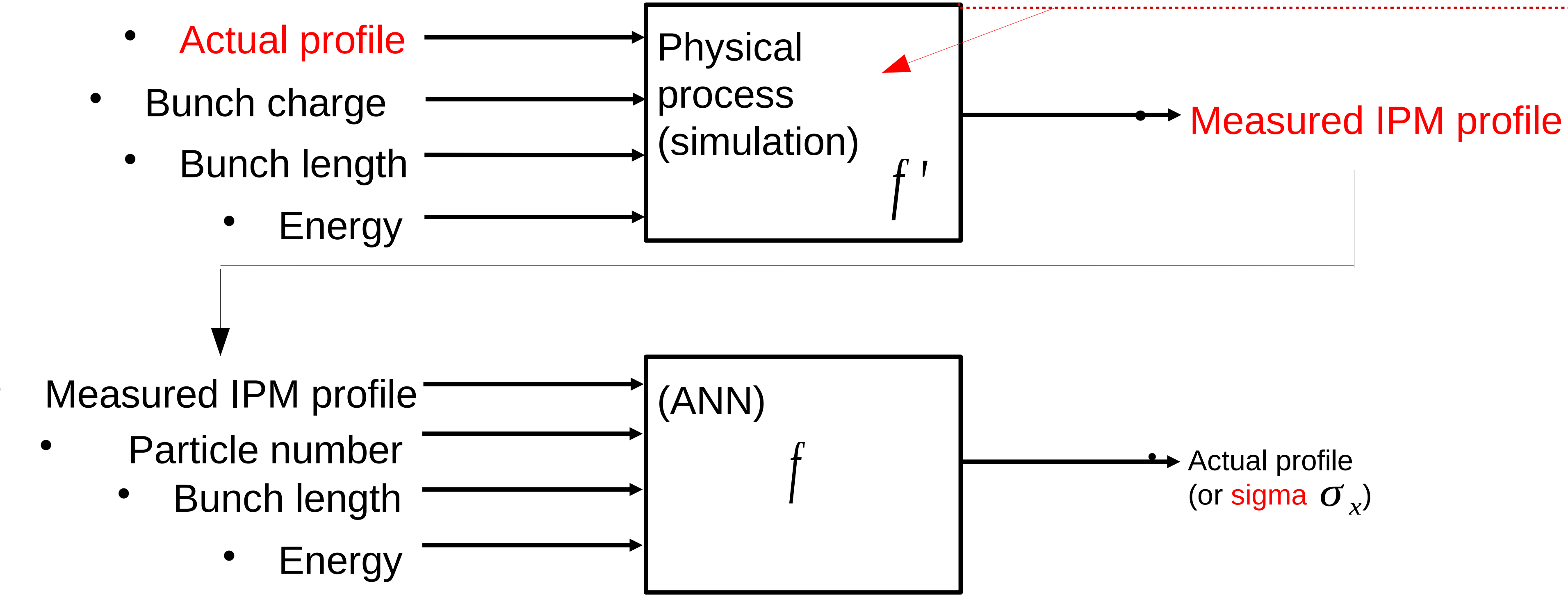
  [eg. R. E. Thern, PAC1987, J. Amundson et al., PRSTAB 6, 102801 (2003)]

  Latest work: Assumption on input beam distribution (Generalized Gaussian) and iterative procedure for input reconstruction from distorted profile using the data generated from simulation tool.

  [Jan Egberts, PhD Thesis, CEA Saclay]

Example 2:
profile correction using ANN

Virtual-IPM: python package, see:
D. Vilsmeier, et al Proc. of IBIC17 , WEPCC07



Training "grid" (375 points):

Using *tensorflow* and *Matlab NN toolbox*

σ_x	0.29, 0.31, 0.33, 0.35, 0.37 (mm)
σ_y	0.4,0.45,0.5,0.55,0.6 (mm)
N_p	1.1e11, 1.25e11, 1.40e11, 1.55e11, 1.7e11
σ_l	0.9, 1.05, 1.2 (ns)

Example 2: Results

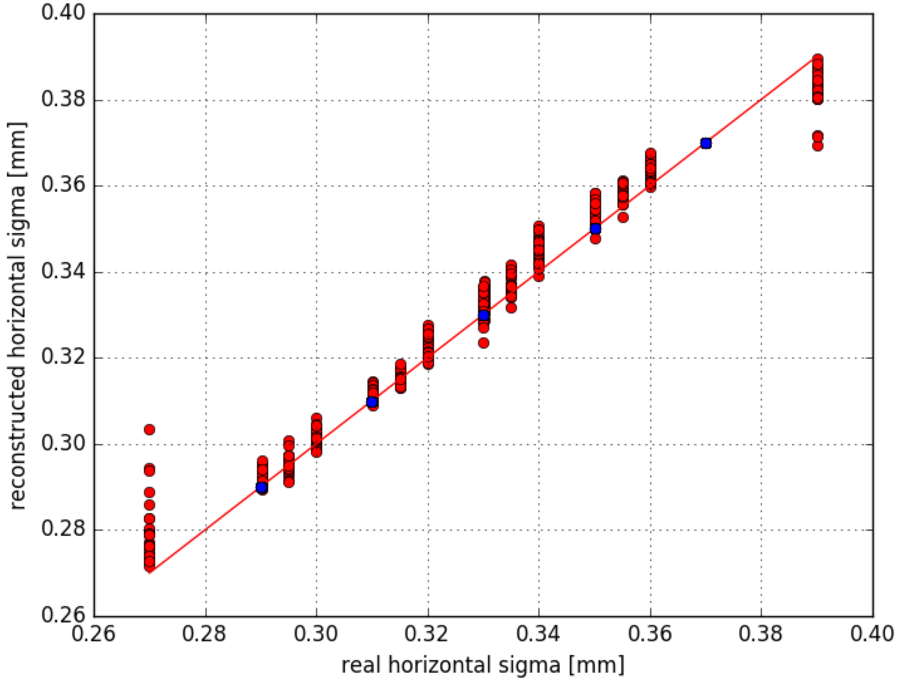
Validation "grid" (128 points)

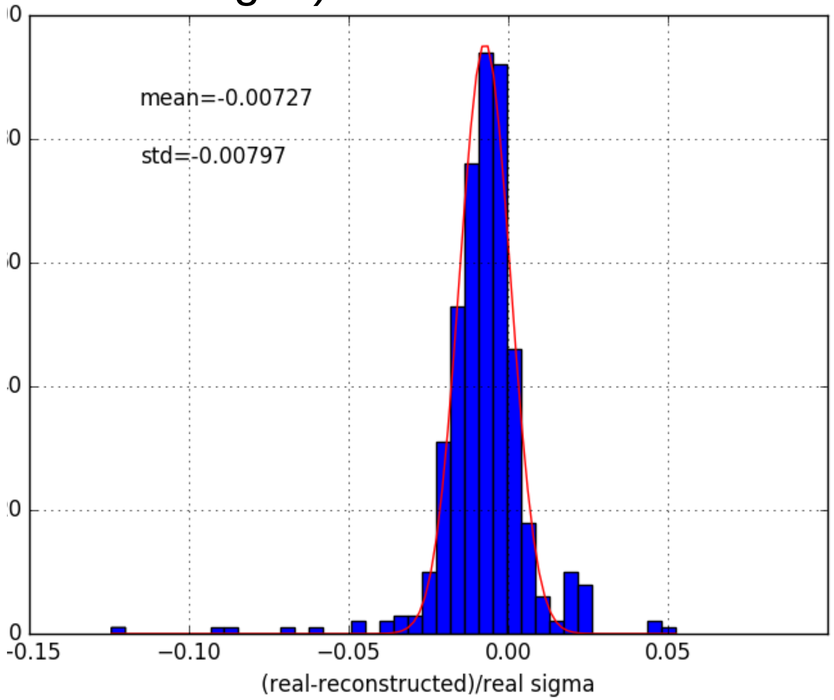
4 validation data sets (inputs and outputs) created:

- 1% off the training grid in each dimension (within in grid)
- 25% off the training grid in each dimension
- 50% off the training grid in each dimension
- 100% off the training grid (the next point outside the grid)

For 12 runs:
sigma systematically overestimated by 0.4% with error 0.8%

Much smaller than measurement errors!

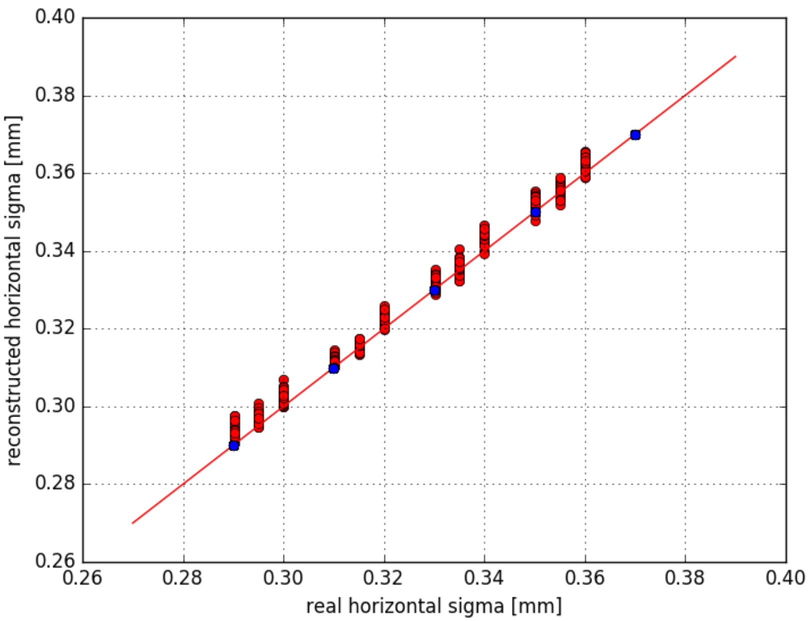


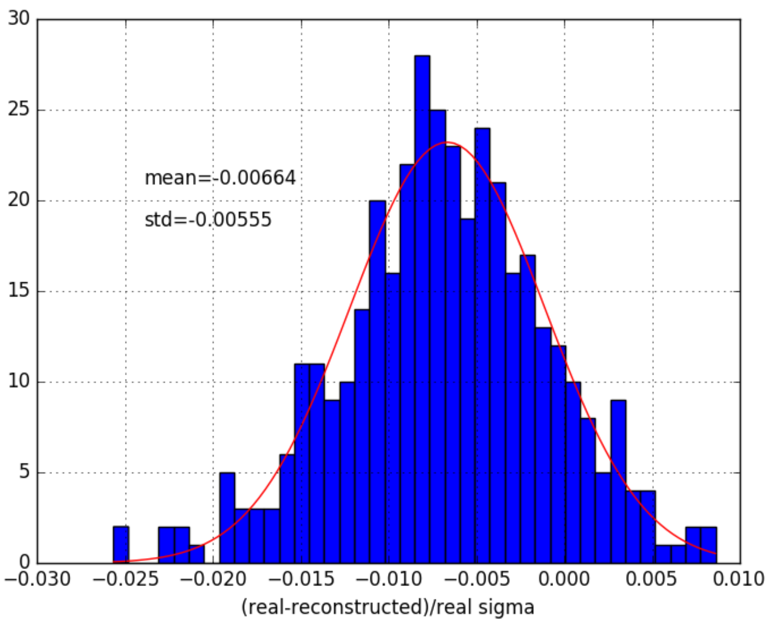


Example 2: Results

Removing the validation sample outside of “training” area

For 12 runs:
sigma systematically overestimated by 0.05% with error 0.7%





IPM profie correction – recent developments

Proceedings of IPAC2018, Vancouver, BC, Canada - Pre-Release Snapshot 06-May-2018 12:00 UTC

RECONSTRUCTING SPACE-CHARGE DISTORTED IPM PROFILES WITH MACHINE LEARNING ALGORITHMS

D. Vilsmeier, M. Sapinski, R. Singh, GSI, Darmstadt, Germany
J. W. Storey, CERN, Geneva, Switzerland

- 4 machine learning algorithms compared: linear regression, kernel Ridge regression, support vector machine and multi-layer percepton

Table 2: Resulting Scores for the Different Models. Values are given in units of 1 μm, 1 μm^2 respectively.

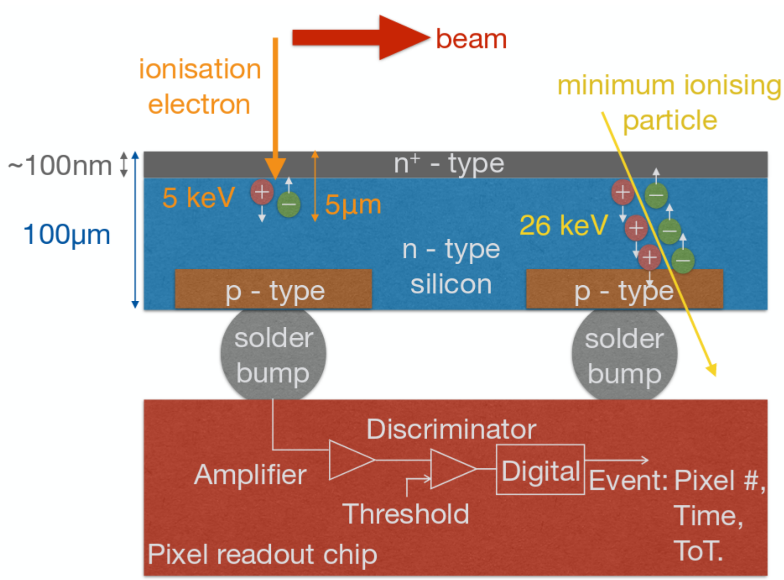
	μ(**res**)	σ(**res**)	**R2**	**EV**	**MSE**
LR	0.012	0.449	0.99976	0.99976	0.201
KRR	0.005	0.340	0.99986	0.99986	0.115
SVR	0.006	0.349	0.99985	0.99985	0.121
MLP	0.232	0.370	0.99977	0.99984	0.190

- Surprisingly even the simplest linear regression works well in theory!

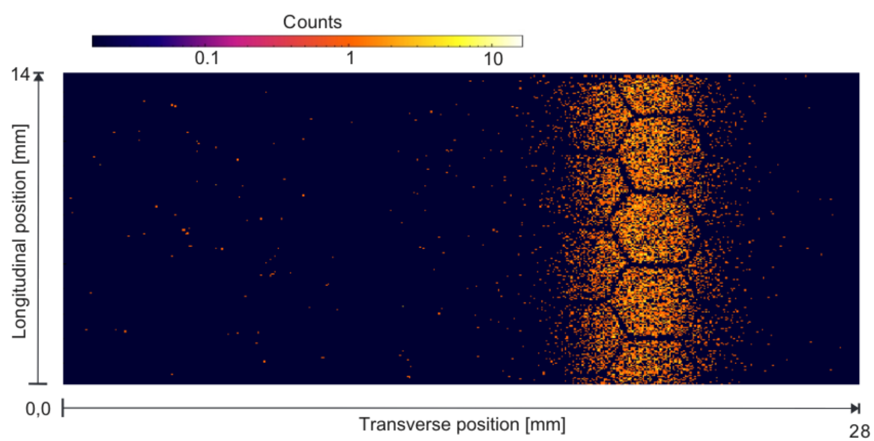
Remark:
New IPM detector technology

- Hybrid silicon pixel detector (in this case Timepix3)
- Relatively inexpensive
- Pixels 55x55 μm^2
- Single chip 256x256 pixels

- Sub-ns timing
- Continous measurement
- Prototype working well on CERN PS
- No capricious MCP

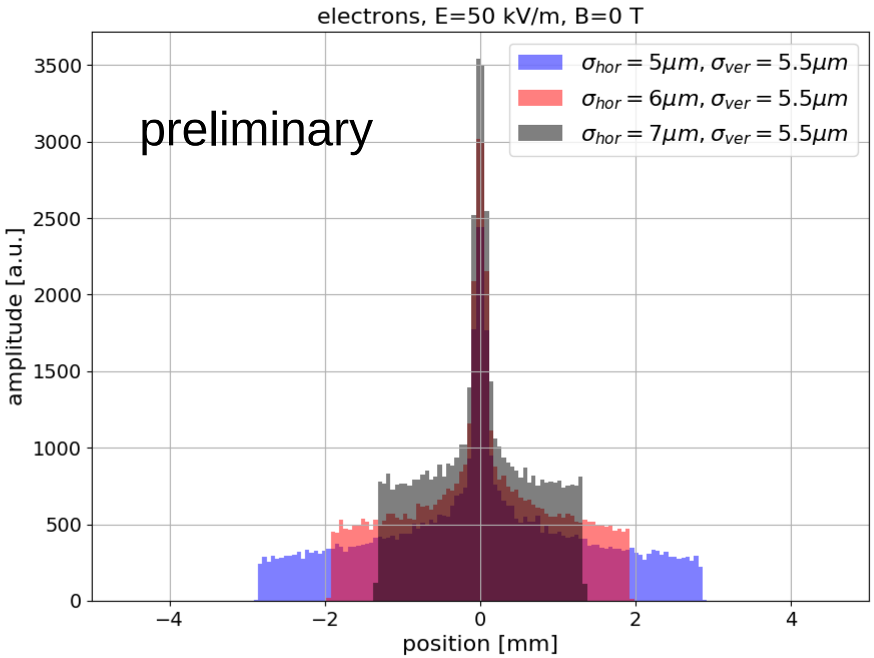


J. Storey et al., Proc. IBIC 2017(WEPCC07)
S. Levasseur et al., Proc of IPAC 2018(WEPAL075)



Remark:
measuring micrometer-size beams

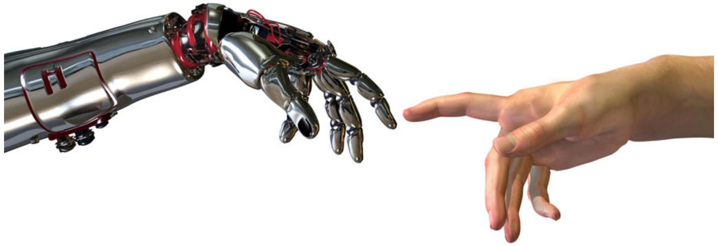
- If we understand the beam profile deformation, we could use it to measure high-brightness beams smaller than the resolution of the detector.
- Example: 5.8 GeV electron beam, 230 pC bunch charge, 21 fs bunch length, 5-7 um transverse size.
- Even if bunch size is 1/10th of detector resolution, the shape of the deformed profile strongly depends on the bunch size!
- Alternative to *R. Tarkeshian et al. Phys. Rev. X 8, 021039*



Conclusions

- ML techniques become a standard tool for physicists and engineers.
- They proof to be efficient in solving non-linear multivariate problems.
- Can save lots of money:

  (CryoBLM project ~1 M€, a set of 1T magnets for IPM ~ 5M€)
- Modern tools (eg. tensorflow+keras) are very easy to use.
- Lot of physicists remain skeptical because “black box” nature of ML and lack of convincing way to estimate errors.
- I think that we should use it but not forget about its limitations and check for simpler solution.



Further reading and playing

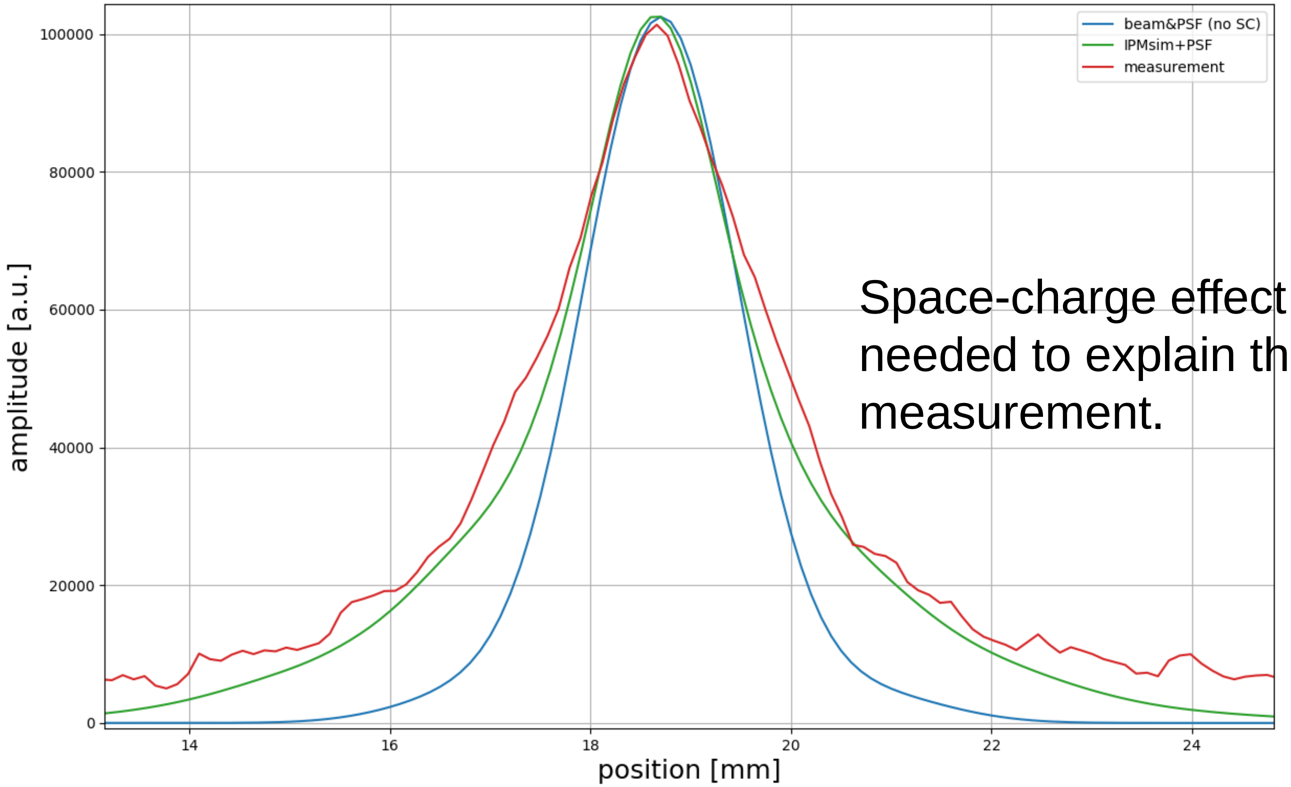
- “How could a Kangaroo climb Everest?” - about minimization algorithms: ftp://ftp.sas.com/pub/neural/kangaroos
- ANN recognizing drawings: https://quickdraw.withgoogle.com
- Music composed by AI: http://www.flow-machines.com/ai-makes-pop-music/
- Unreasonable effectiveness of ANN: http://karpathy.github.io/2015/05/21/rnn-effectiveness/
- E. Musk concerned about AI: https://www.youtube.com/watch?v=0NTb10Au-Ic
- AI algorithms in social media – very interesting: https://www.ted.com/talks/zeynep_tufekci_we_re_building_a_dystopia_just_to_make_people_click_on_ads
- ANN playing with images:
- https://nerdist.com/why-are-googles-neural-networks-making-these-brain-melting-images
- …

Acknowledgments:

A. Reiter, P. Forck, J. Storey, K. Sato,
D. Reggiani

Additional slides

Space-charge on SPS beam



Space-charge effect clearly needed to explain this measurement.

Artificial Neural Networks - Overview

Approximate target function

$$o_i = g\left(\sum_{j=0}^{M} W_{ij}\left(g\left(\sum_{k=0}^{N} x_k W_{jk} + b_j\right)\right) + b_i\right)$$

Solve optimization problem with training data

STO

$$E = \sum_{i=0}^{L} (y_i - o_i)^2 + \lambda \sum_{j=0}^{M} \sum_{k=0}^{N} (W_{ij})^2$$

Calculate gradient, update weights

$$\frac{\delta E}{\delta W_{ij}} = a_j Err_i g'(inp_i)$$

$$W_{ij}(t+1) = W_{ij}(t) + \alpha \frac{\delta E}{\delta W}$$

Validate with other data, “validation data” to check the generalization or “learning”

If not, change the number of units or architecture

- Supervised learning, unsupervise learning, reinforcement learning
- Batch learning, incremental learn
- Functions: Activation function, Target function, Objective or erro function
- Optimization: Gradient descent, Levenberg-Marquardt, Epoches, Learning rate, Momentum

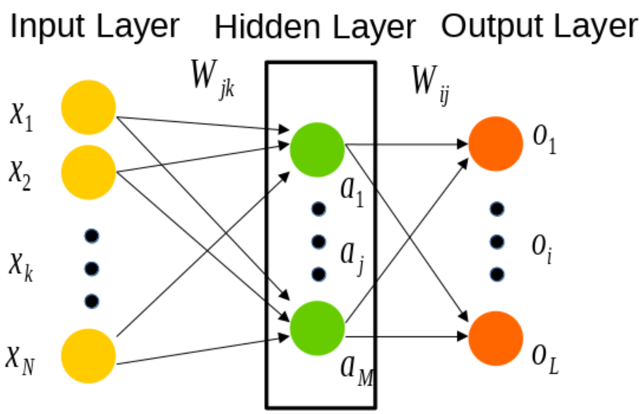
For more: How could a Kangaroo climb Everes

- ftp://ftp.sas.com/pub/neural/kangaroos
- Generalization: Cross validation, regularization, early stopping

The big goal:
Artificial General Intelligence

- AGI (or “strong AI”) - mimicking (or overperforming) human in any intellectual task
- Include: computer vision, natural language communication, etc, etc...
- Brain simulation (Blue Brain Project) versus Neuromorphic computing architectures (HBP Human Brain Project)
- Some belive/fear that AGI is next step of evolution (“Person of Interest”, E. Musk, S. Hawking… etc, etc)

Calculating backpropagation



$$o_i = g\left(\sum_{j=0}^{M} W_{ij}\left(g\left(\sum_{k=0}^{N} x_k W_{jk} + b_j\right)\right) + b_i\right) \quad = g(s)$$

$$E = \sum_{i=0}^{L} (y_i - o_i)^2 \quad -> \quad E = (y - o)^2$$

$$\frac{dE}{dW_{11}} = \frac{dE}{do} \cdot \frac{do}{ds} \cdot \frac{ds}{dW_{11}}$$

-2(y-o) g'(s) a_1

$$\frac{\delta E}{\delta W_{ij}^{1}} = a_j \, Err_i \, g'(inp_i)$$