Machine learning for accelerators
A physicist approach

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Contents

Machine learning

- approaches
  - learn to reproduce: "supervised learning" (e.g. regression)
  - find structure: "unsupervised learning" (e.g. isolation forests)
  - learn environment: "reinforcement learning" (e.g. AlphaGo)
- concepts
  - Random variables, statistic distribution
  - prior, posterior, Bayes rule
  - additive models, trees networks
  - Bellman's equation

We are drowning in information and starving for knowledge

– Rutherford D. Roger

Machine Learning is about learning from the data, not about application of a particular "intelligent" technique.

– Elena Fol, IPAC'20

Machine learning

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„Fliegen tut auch ein Scheunentor, wenn der Motor nur gut ist."[1]

Simon Brunnhuber

"With a big enough engine you can make a barn door fly"

Regularisation

- slow orbit feedback: Thikonov regularisation, finding orbit distortions, sklearn

Example

Orbit feedback

- Read orbit deviation
- Calculate correction → on diagonal → ridge

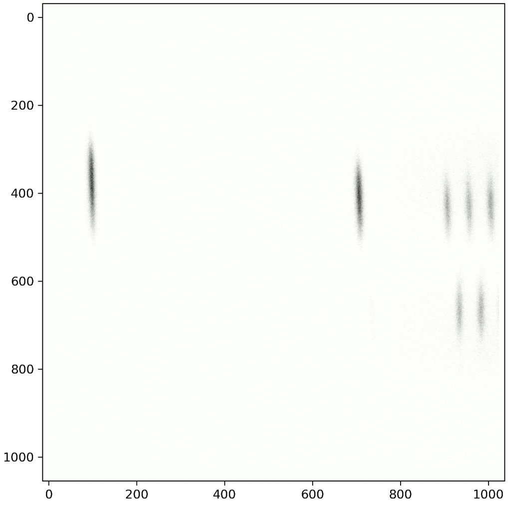
```
# bpm signals
b_A = np.array([x_bpm, y_bpm]).ravel()

# orbit response matrix
corr_mat = self.orb.get()
alpha = self.alpha.get()

# sci kit learn: regularisaton of the central diagonal
self.ridge = Ridge(alpha=alpha)
self.ridge.fit(corr_mat, b_A)
pos_corr = self.ridge.coef_
```

- Streak camera measurement
- Identify spots

```
x, y = np.fromfunction(lambda y,x: (x,y), im.shape)
val = im.ravel()
# Points above threshold
xr = x.ravel()[val>threshold]
yr = y.ravel()[val>threshold]
X = np.array([xr, yr]).T
# Make spots rather round ...
X_trans = X * np.array([1, .2])[np.newaxis, :]
y_pred = KMeans(n_clusters=7, random_state=0)
          .fit_predict(X_trans)
```



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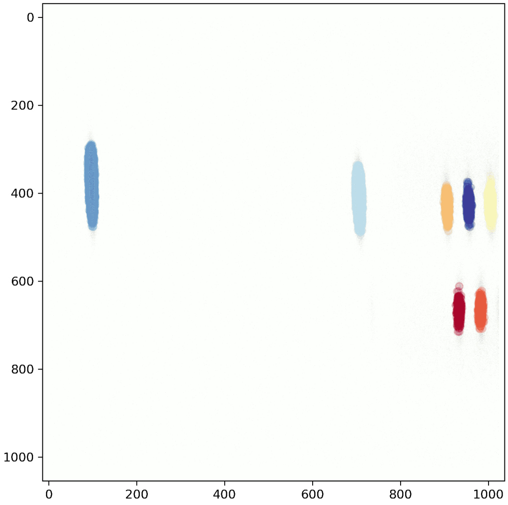
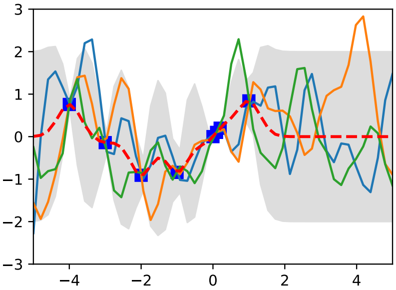


Gaussian process

Power of a simple idea

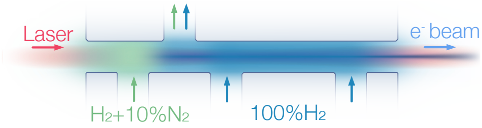


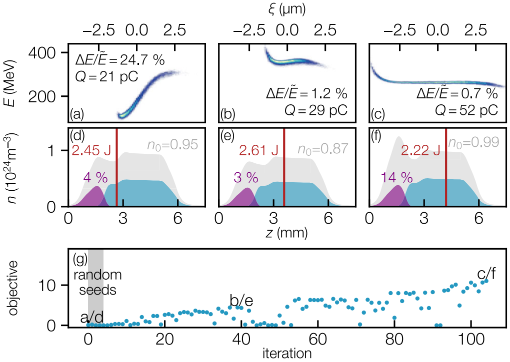
- Linear regression → minimum distance
- Bayesian approach: most probable line
- Idea taken further:
  - Set of probable functions
  - covariance between functions
  - characteristic length

  }

  - data points → most probable function
  - covariance → confidence bound
  - further probing: most probable one (add noise for exploration)

Gaussian process: laser plasma optimisation





Focus position: *target length 5 mm / 0.05 mm = 100x*

Doping: *0 to 100 % / 1 % = 100x*

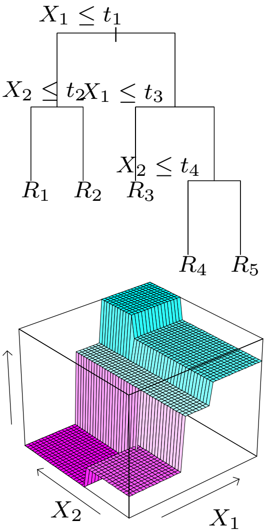
Gas density: *0.5x10^{18} to 1x10^{18} cm^{-3}/0.05x10^{18} cm^{-3}= 10x*

Laser energy: *2 J to 3 J / 0.1 J= 10x*

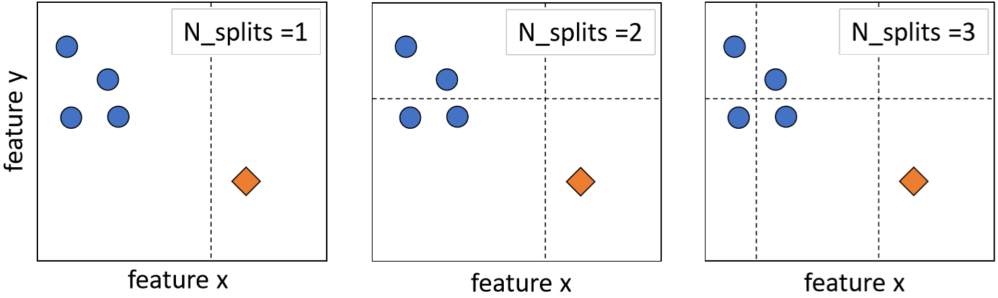
Sören Jalas et al., "Bayesian Optimization of a Laser-Plasma Accelerator" [1]

Trees

- Splitting fields in "common areas"
- Learning: when to split using which variable
- Boosting: chain trees: have next one predict residuals from the previous ones
- Random forests: tress split randomly, combine results → outliers Isolation forests



Example: BPM cleaning at LHC



- Target: identify "broken" BPMs
- Forest: split up
- Isolation forests: randomly split many times → outliers split of early

See E. Fol et al. "Detection of faulty beam position monitors using unsupervised learning", [2] [3]

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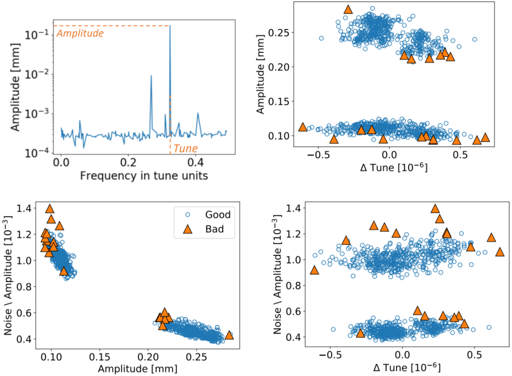

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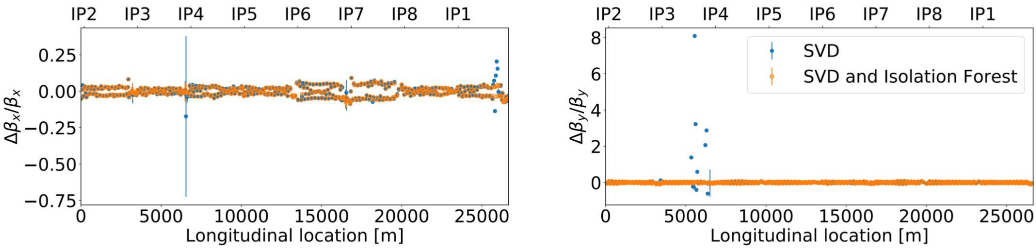

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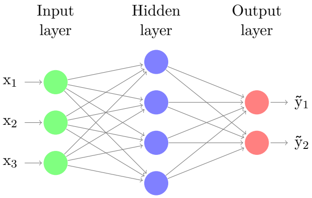
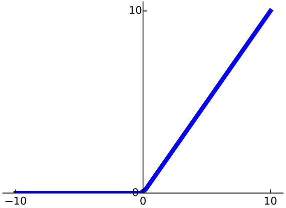
Network I/II

- Simple basis functions with weights
- network of functions → complex task
- inference (prediction) → forward pass
- learning (“fit network to data”) → backward pass: networks with gradient
- convolution: learn to combine data
- long short term memory: learn from history, but also when to ignore history!

- Layers of neurons: processing units
- activation functions: select range, weight
- build automatically gradient
- flexible, large set of parameters
- trained on large datasets → processed in batches





ReLU

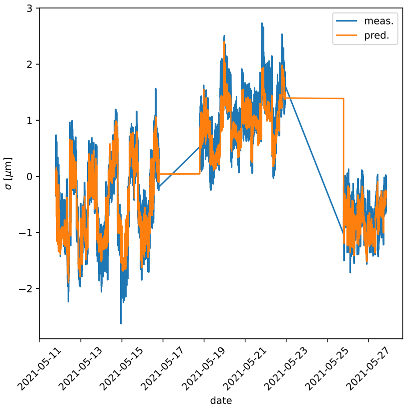
LSTM for beam size

- Light source: beam size → tight control, beam size influenced by emittance exchange horizontal → vertical ALS [4]:
- target: insertion device change → feed forward
- data showed: effect delayed → LSTM

```
from tensorflow.keras import Input
from tensorflow.keras.models import Model
from tensorflow.keras.layers import LSTM, Dropout, Dense
from tensorflow.keras.optimizers import Adam

inputs = Input(shape=(60, 152))
x = LSTM(128, return_sequences=True)(inputs)
x = Dropout(0.1)(x)
x = LSTM(64, return_sequences=True)(x)
x = Dropout(0.1)(x)
x = LSTM(32, return_sequences=False)(x)
x = Dropout(0.1)
outputs = Dense(1)

model = Model(inputs=inputs, outputs=outputs, name='vertical_beam_size')
```



Courtesy: Alexander Schütt

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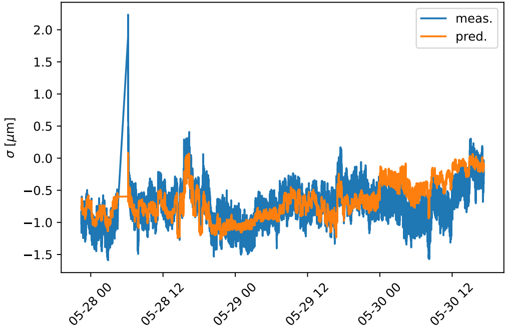

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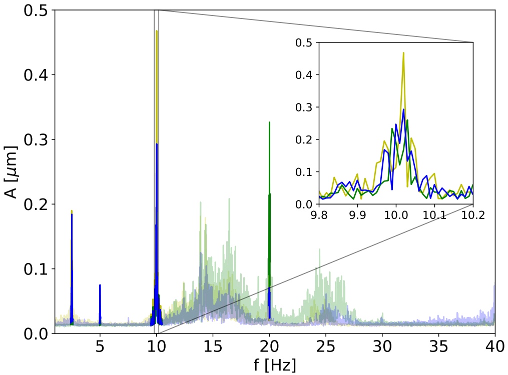
Reinforcement learning: motivation

- Markov decision process: current state → predict future (e.g. chess game)
  - actor (controller) → applying actions (control signal)
  - environment (plant) → state
  - rewards
- Learning
  - actor: policy → how to play (e.g. chess: next move)
  - value function: long term reward for actions (e.g. chess: move more likely to win)
- learning: long term outcome, estimate variation
- solution found: Bellman's equation → sufficient each step optimal
- control learned "playing games": good nerves when operating on beam → explainable AI

Orbit optimisation

- Harmonic orbit distortion
- no action: yellow
- classical: steerers → orbit response matrix → SVD → correction
- Here: SVD + reinforcement agent

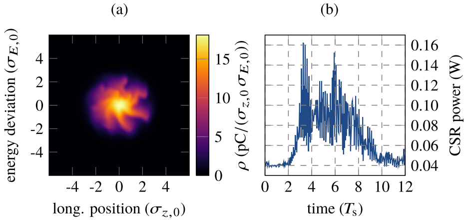
See Luis Vera Ramirez THAL01

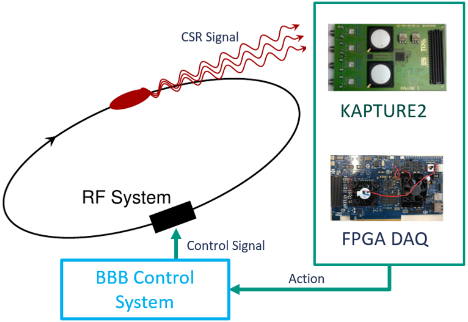


Coherent synchrotron radiation control

Development KIT/KARA

- Synchrotron light sources:
  - deflected electrons → emit light
  - short bunches → coherent light emission → ↑ Power → destabilises bunch
  - mitigation: RF control ← reinforcement learning
  - dedicated hardware → ≈ 10 μs [5]





Explainable machine learning

Accelerators: expensive device → beam experiment access: precious resource: e.g. broken beam position monitor → effect on controller

- Network learns problem → black box
- Explore black box

- find simplified model: e.g. statistical learning one
- train model using original data and trained network
- understand network's behaviour

Methods

- Local interpretable model-agnostic explanations (LIME)[6]: behaviour local area in neighbourhood
- SHAP(ly) values[7] → prediction of cooperative players → influence of different features

Non learning part

Life cycle

- Data access
- Algorithm
- Deployment
- Monitoring

Time

- learning: data sources: consistent time
- interaction: minimize delays
- new installations: steady state machines $\rightarrow$ transient ones

Data quality

- constient access (archivers)
- metadata, calibration
- data cleaning, scaling

Deployment

- accelerators: lifespan $>$ 30 years
- software stack: technical debts $\downarrow$: minimise dependencies e.g. notebooks $\rightarrow$ input output controllers
- versioning, roll back

Conclusion

- (Short) overview over methods and fields
- More details: following talks today, conference
- Let data science experiment $\rightarrow$ reveals new insight
- Domain $\leftrightarrow$ data science: closely work together: exchange
  - knowledge
  - experience
  - best practise

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- Thanks to Luis for tutoring, introduction materials
- Tom discussion on statistical methods
- Support of BESSY II
- all not even mentioned

For new bees

- Just try it! → first solutions applying examples to your data e.g. scikit-learn
- Networks: published solutions → your data → useable solutions
- well documented libraries: ← “optimisers” self implemented Netwon, Brent?
- contribute: your results, your success stories

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