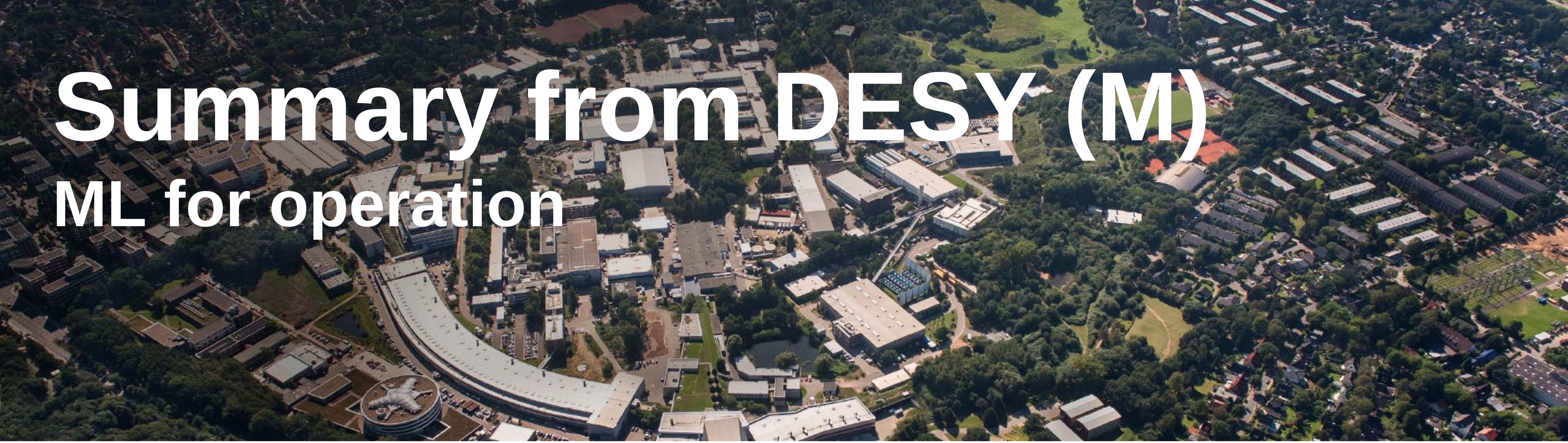


Summary from DESY (M)

ML for operation

ACCLAIM

Annika Eichler

25.06.2021

HELMHOLTZ RESEARCH FOR GRAND CHALLENGES

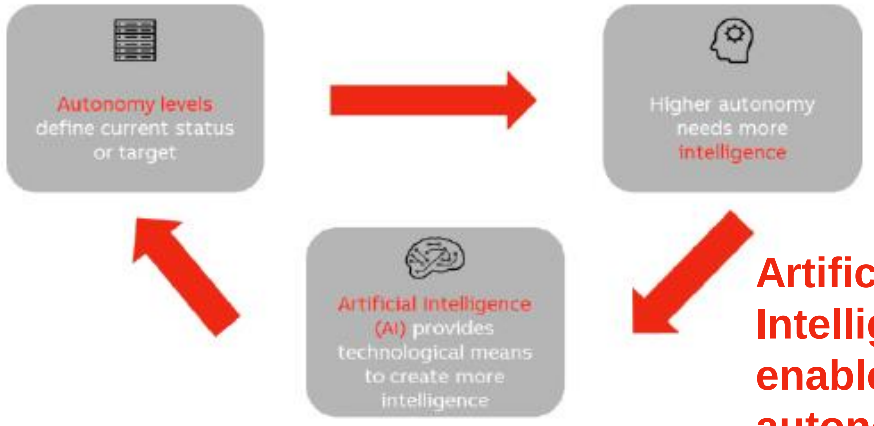
DESY.

ML as enabler for autonomy

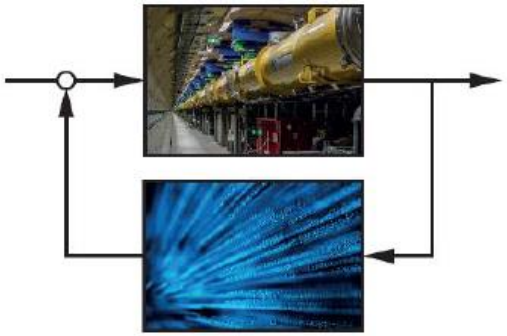
Topics of research

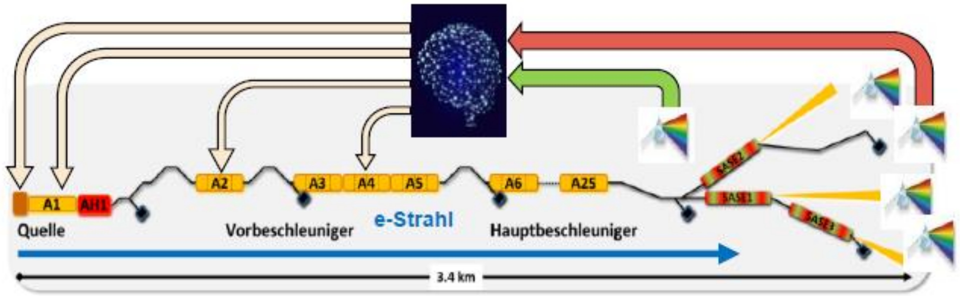
- **Data acquisition and data analysis (pipelines)**
  - Get all relevant signals and provide understanding
  - Provide data infrastructure
- **Fault diagnosis and supervisory control**
  - Predict faults, prevent failures
  - Protect the system
- **(Surrogate) modelling, simulations, digital twins**
  - Understanding physics
  - Requirement for predictions, development and control
- **Optimization and feedback control algorithms**
  - Push the way of operation
  - Optimize performance

T. Gamer et. al., "The autonomous industrial plant -future ofprocess engineering, operations and maintenance," 12th IFAC Symposium DYCOPS, vol. 52, no. 1, pp. 454–460, 2019.



Artificial Intelligence as enabler for autonomy

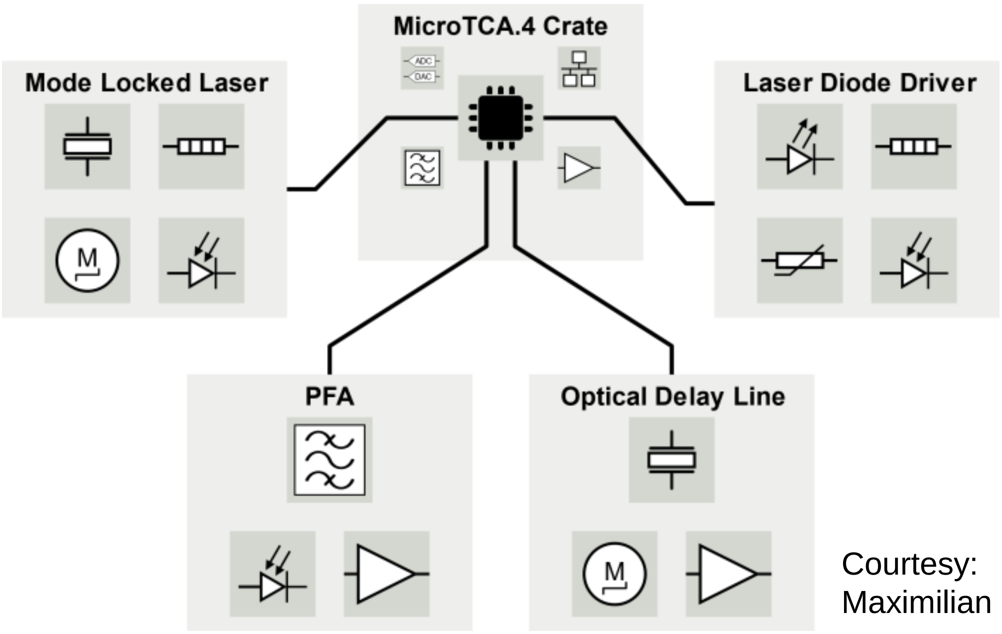




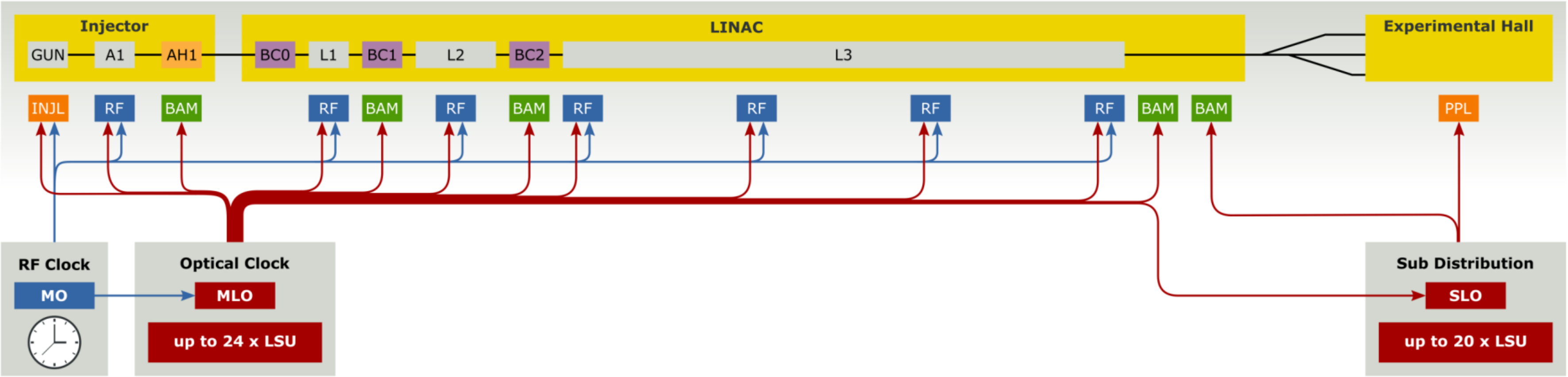
Data acquisition and data analysis (pipelines)

Get all relevant signals and provide understanding

- **Long-term DAQ system for a subsystem:** Build a complete long-term data acquisition system for the optical synchronization system at European XFEL
  - Data scope:
    - 50’000+ data channels (configuration + monitoring),
    - In total > 150 MB/s data to data acquisition system
      → Data reduction necessary (to meet 100 TB/y)
    - ~ 1% of the European XFEL



Courtesy:
Maximilian Schütte

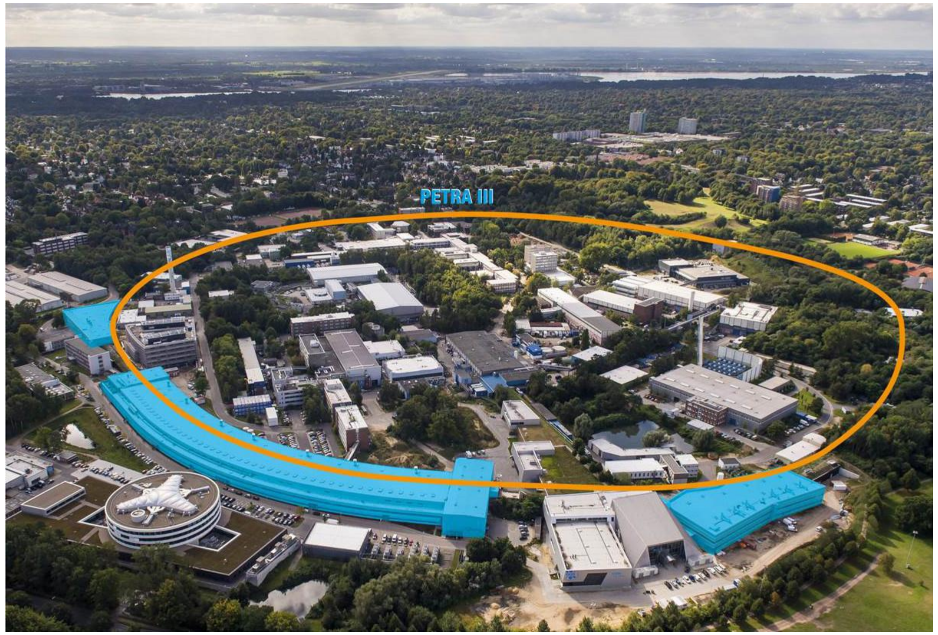


Data acquisition and data analysis (pipelines)

Get all relevant signals and provide understanding

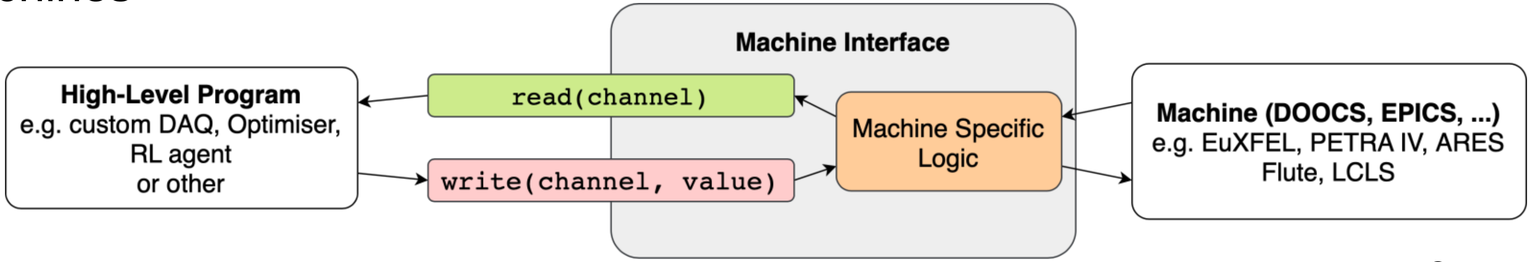
- **Data analysis and control pipeline:** for supporting decision-making and analysis of beam optics, first test at PETRA III based on kafka (M. Boese, I. Agapov)

kafka



© DESY

- **Standardize interfaces:** between algorithms and simulations / machines
(J. Kaiser, O. Stein)

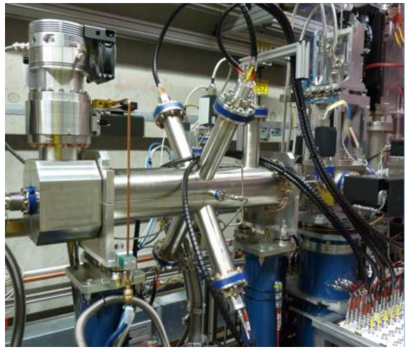


Courtesy Jan Kaiser & Oliver Stein

Data acquisition and data analysis (pipelines)

Get all relevant signals and provide understanding

- **OPIS@FLASH2/DESY: ML for single-shot FEL pulse characterization (DESY FS-FLASH / HZB)**
  - FEL wavelength measurement using photoelectron TOF spectroscopy
  - Problem : poor signal/noise for single-shot analysis/monitoring



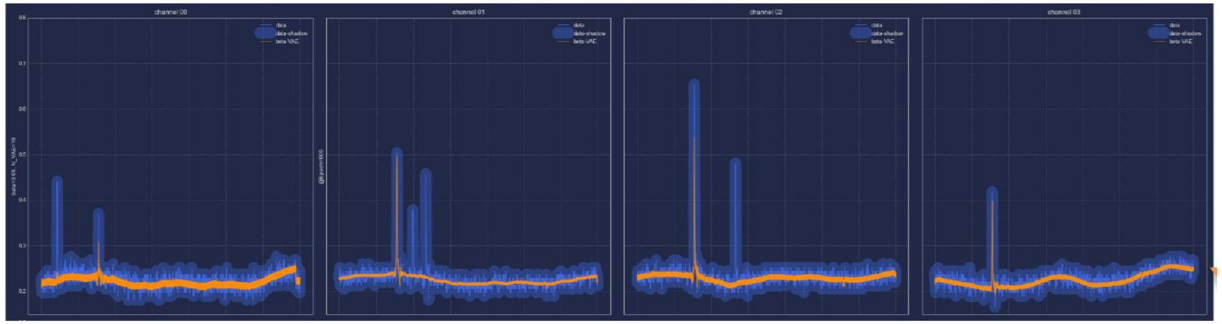
Braune et al., JSR **25** (2018)

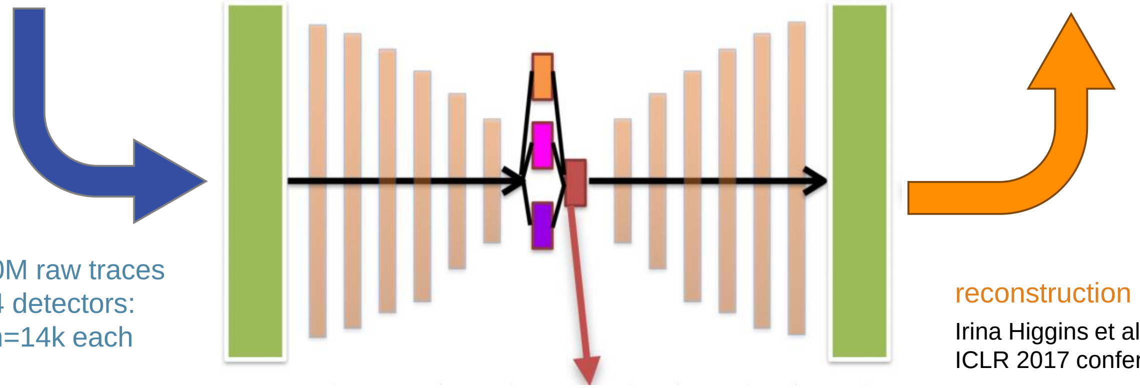
Involved facilities: **Users:**

M.Braune
S.Düsterer
S.Palutke

G.Hartmann
et al.

M. Gühr
et al.





300M raw traces
of 4 detectors:
dim=14k each

reconstruction

Irina Higgins et al.,
ICLR 2017 conference

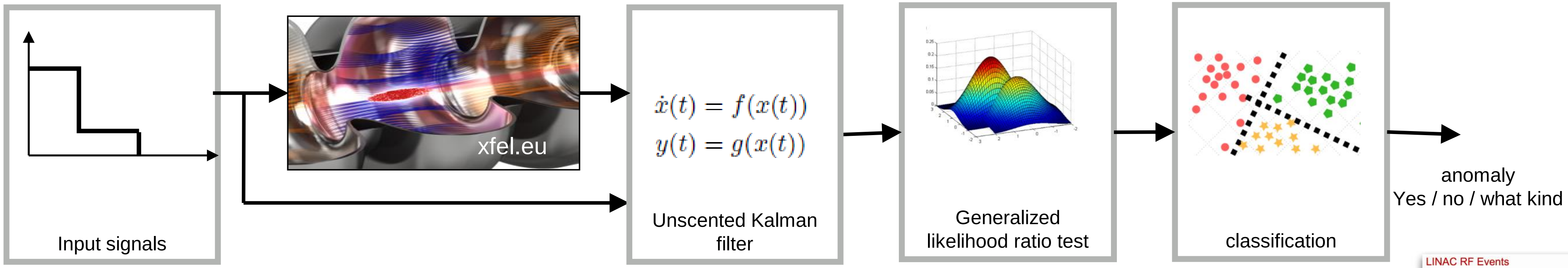
ML Project: neural network with β-variational auto-encoders

- reduce ADC traces to a representation with physical meaning (peak center, …)
- reduce dimensionality → data compression
- eliminate artefacts, background, random events, space charge effects, …

Fault diagnosis and supervisory control

Predict faults and protect the system

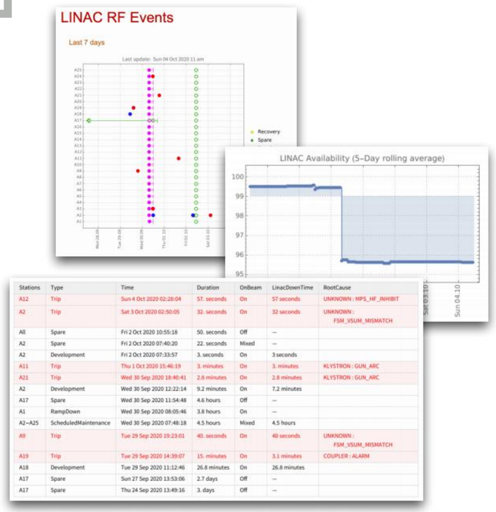
- **Anomaly detection:** for SRF cavities at European XFEL (1.5 GB/s) (Ayla Nawaz)
  - Online implementation of anomaly detection: Trip event logger (Online trip analysis, 18 MHz sampling frequency) (Jan Timm)



Courtesy Ayla Nawaz

- **Root-cause analysis:** (XFEL linac automated trip analysis) (Nicholas Walker)

- **Health Monitoring:** Laser health monitoring with clustering based on abnormal behavior in laser oscillation (H. Hoffmann)

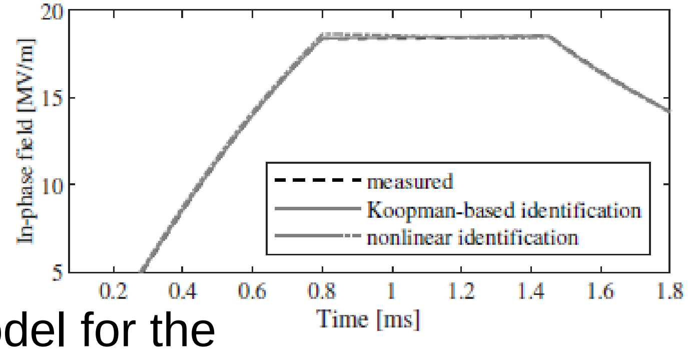


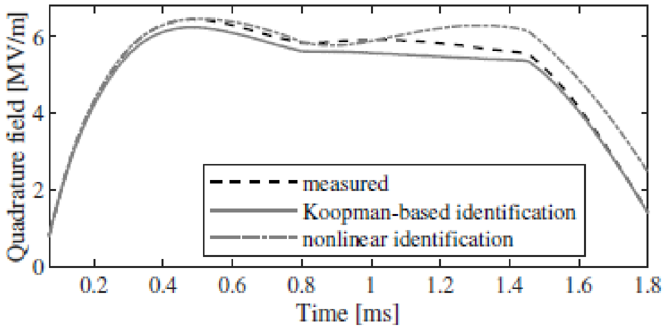
Courtesy Nicolas Walker

(Surrogate) modelling, simulations, digital twins

Understanding physics, requirement for predictions, development and control

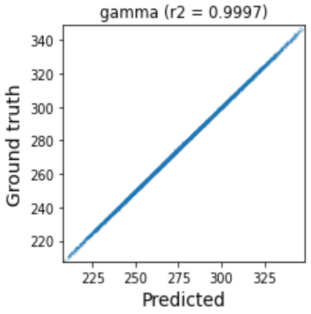
- **Modelling for model-based control / diagnosis:** Data-based nonlinear modeling exploiting physical understanding by Koopman operator theory for SRF cavities at European XFEL (W. Haider, A. Eichler)
  - More precise model as grey-box one
  - 1000 times faster in evaluation for fault detection (Kalman filter)
  - Set-point independent



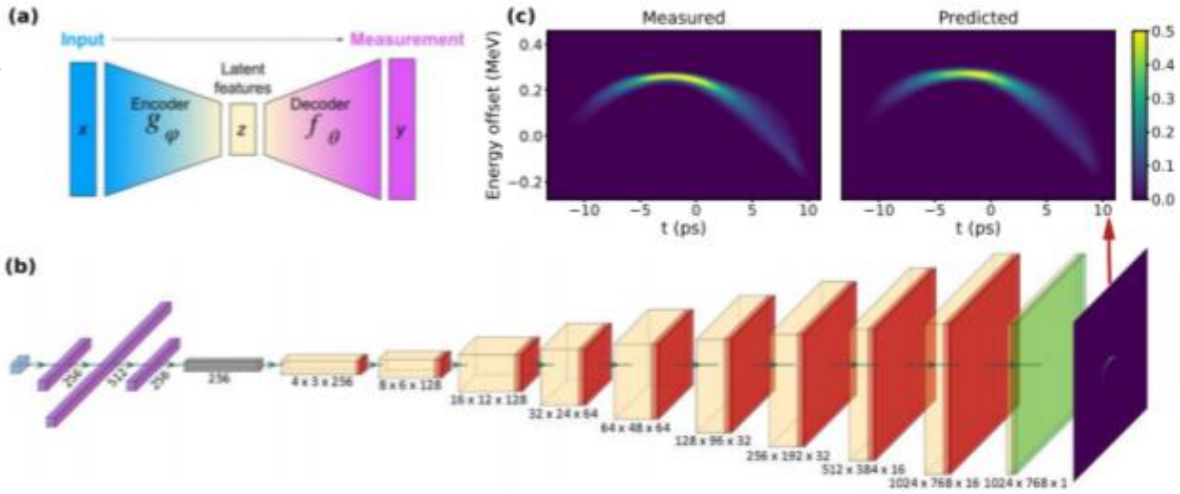


- **Modelling for fast simulations:** Surrogate model for the injector of European XFEL using neural networks (J. Zhu)
  - High-throughput and low-latency applications using hardware acceleration (e.g. Versa ACAP) (with G. Fey, A. A. Zoubi, G. Martino from TUHH)

Prediction result with surrogate model using simulated data



Experimental demonstration of high-quality mega-pixel image prediction



Courtesy Jun Zhu

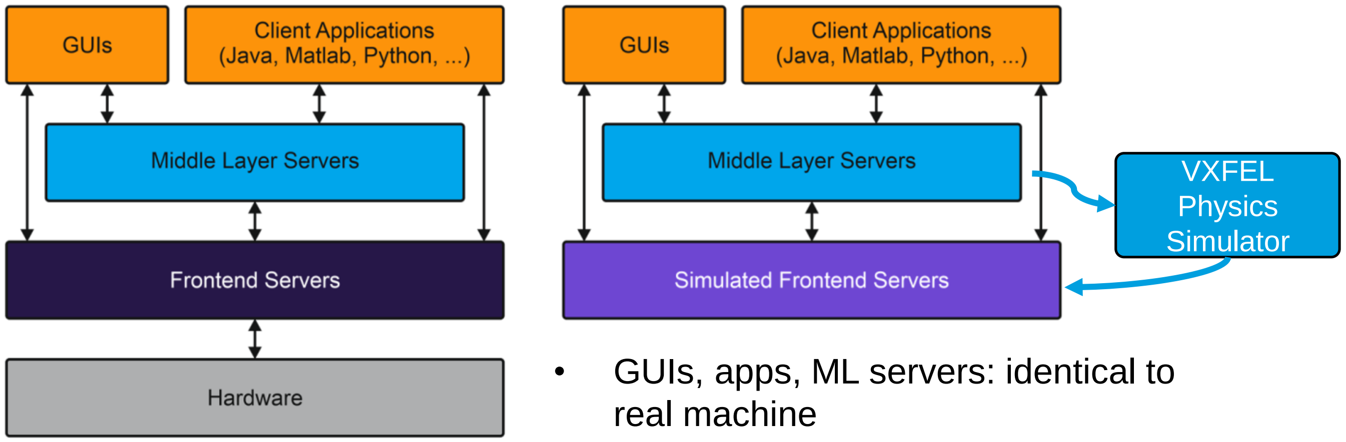
(Surrogate) modelling, simulations, digital twins

Understanding physics, requirement for predictions, development and control

DiGITAL TWINS – The Virtual XFEL & S2E

The VXFEL is a *copy* of the accelerator control system

- … to test software, procedures, algorithms
- … before the real machine is available
- … while the real machine is in operation
- … when it is too hard to test on the real machine



- GUIs, apps, ML servers: identical to real machine
- Simulated frontend servers instead of access to hardware

VXFEL Physics Simulation

- Single-particle tracking through multiple branches of the accelerator
- Outputs:
  - Beam position, Charge (full transmission up to $|x|^2 + |y|^2 > r_{max}^2$), Screens with Gaussian beam spots
- Tracking in "real-time" at 10 Hz

Start-To-End Simulations (S2E)

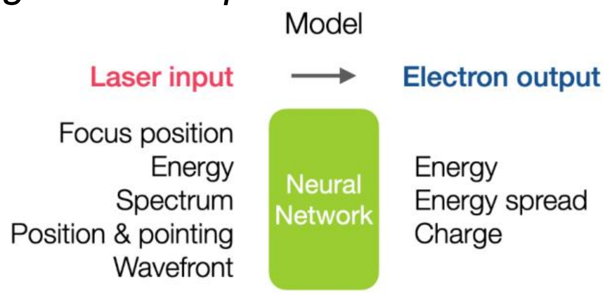
- Tracking simulated particle bunches from the gun to a point of interest (e.g. an undulator)
  … to understand how to improve beam quality
  … to optimize machine parameters
  … to explain observed beam behavior or predict it

Lars Fröhlich et al., DESY

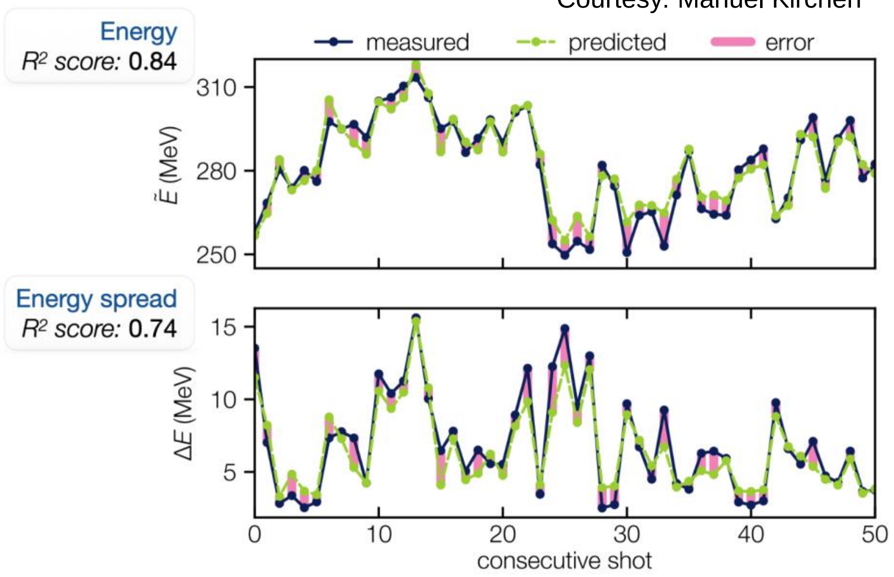
(Surrogate) modelling, simulations, digital twins

Understanding physics, requirement for predictions, development and control

- **Neural network based surrogate model of LPA experiment**
  - Data from LUX laser-plasma accelerator trains a surrogate model and enables single-shot predictive modeling of the plasma electron properties
  - Paves the way for active feedback + stabilization and virtual diagnostics
  - *M. Kirchen et al., "Optimal beam loading in a laser-plasma accelerator" PRL 126, 174801 (2021)*



Courtesy: Manuel Kirchen

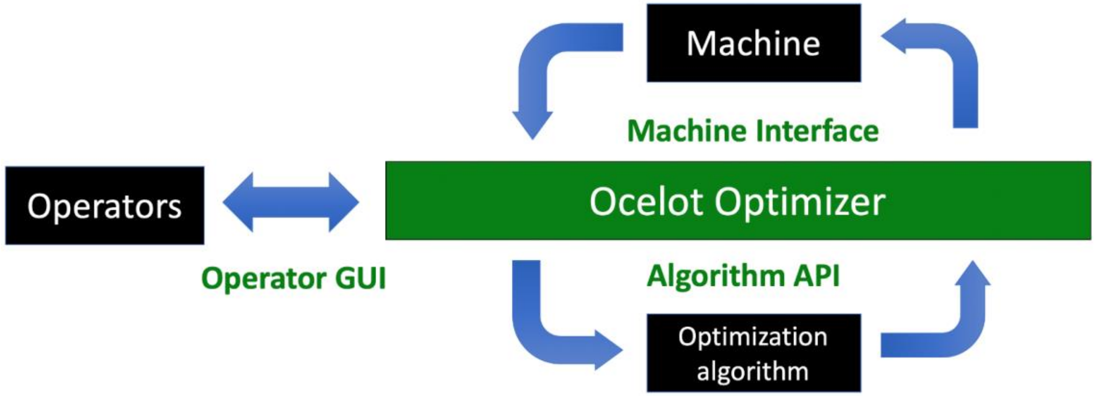


- **OCELOT:** Multiphysics simulation toolkit (already started in 2014) (S. Tomin/ I. Agapov)
  - Charged particle beam dynamics module (CPBD)
  - Native module for spontaneous radiation calculation
  - FEL calculations: interface to GENESIS and pre/post-processing

Optimization and feedback control algorithms

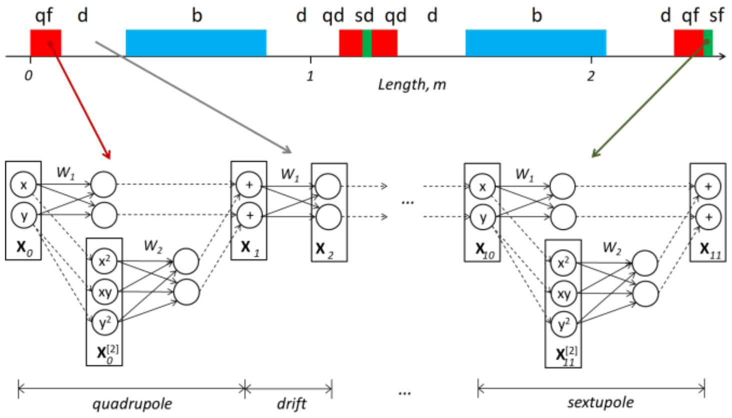
Push the way of operation, optimize performance

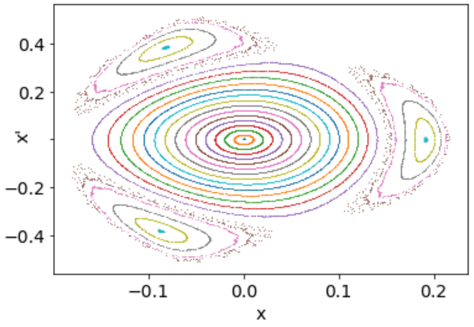
- **OCELOT Optimizer:** Platform for automated optimization of accelerator performance
  (S. Tomin/ I. Agapov)



https://github.com/ocelot-collab/optimizer

- **Physics-based deep neural networks:** NN-based beam adjustable orbit and optics control for storage rings* (A. Ivanov, I.Agapov)





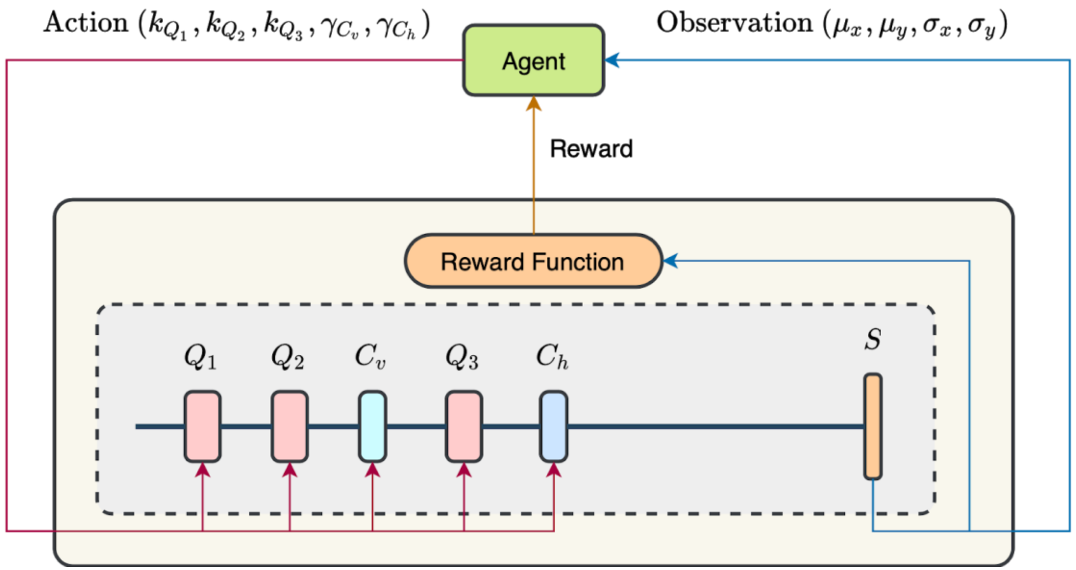
Courtesy Andrei Ivanov

* Andrei Ivanov and Ilya Agapov, “Physics-based deep neural networks for beam dynamics in charged particle accelerators”, Physical Review Accelerators and Beams 23, 07461 (2020)

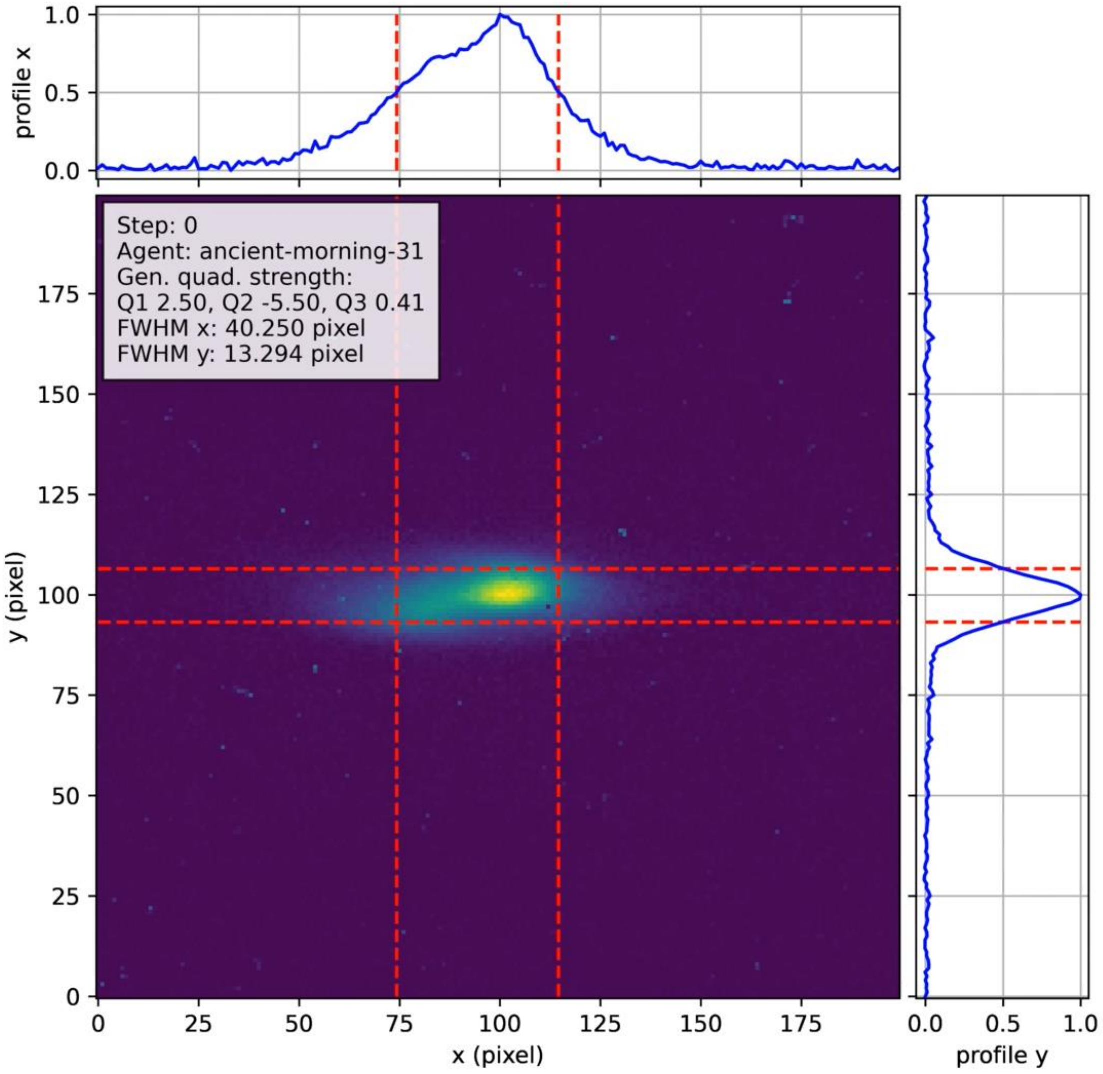
Optimization and feedback control algorithms

Push the way of operation, optimize performance

- **Reinforcement Learning for beam focusing :**
  First steps of applying RL for beam focusing at ARES, collaboration project with KIT (J. Kaiser, O. Stein, A. Eichler)



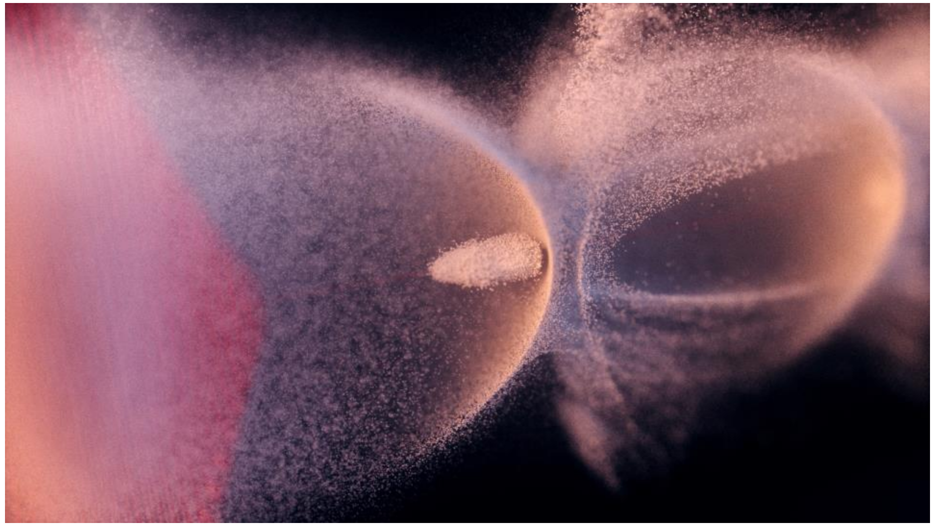
Courtesy Jan Kaiser & Oliver Stein

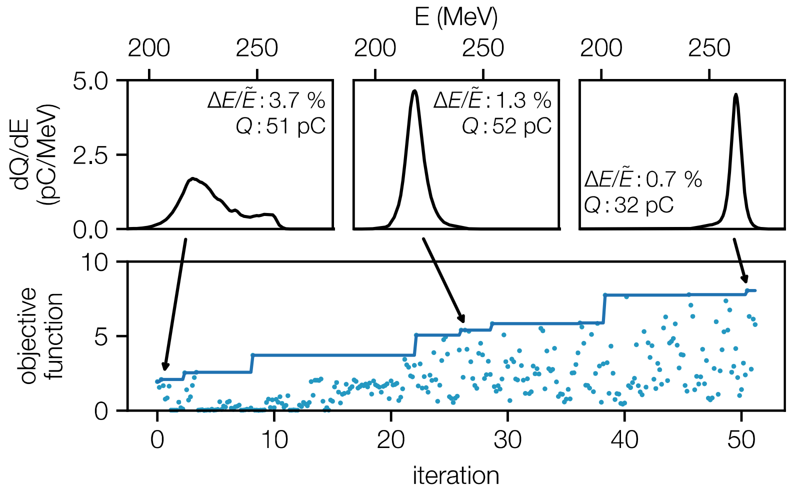


Optimization and feedback control algorithms

Push the way of operation, optimize performance

- **Machine Learning of Laser-Plasma accelerators:**
  Surrogate modeling and Bayesian optimization at LUX
  - **Optimization of electron beam parameters**
    - LUX laser-plasma accelerator tunes to sub-percent energy spread beams using Bayesian optimization
    - *S. Jalas et al. “Bayesian optimization of a laser-plasma accelerator” PRL 126, 104801 (2021)*





Credits:DESY/SciCom Lab
Courtesy: Sören Jalas

Thank you

Contact

DESY. Deutsches Elektronen-Synchrotron

www.desy.de

Annika Eichler
MSK
annika.eichler@desy.de
+49 (0)40 8998 4041