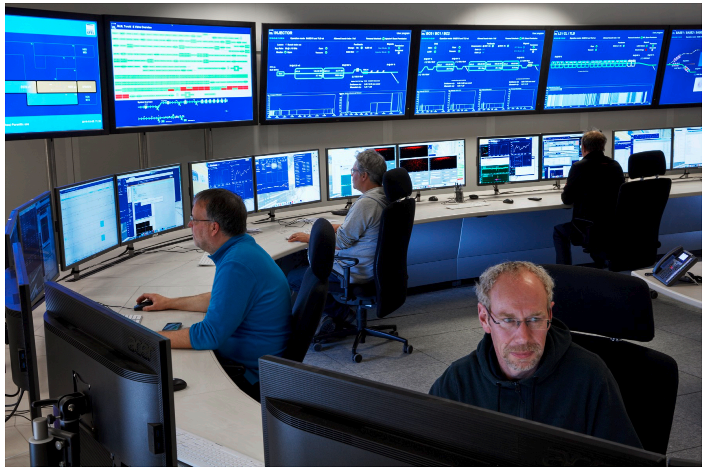
AI technologies
towards autonomous accelerator operation

I. Agapov, 4.12.2020, ML round table at DESY

Objectives

- Ever more demanding stability, reliability and performance goals
- More challenging facilities with more control parameters (PETRA IV)
- Higher photon fluxes -> higher throughput -> need more automatic sample change/wavelength change/beamline setup etc.
- Remote and autonomous operation as the goal for the near future
- Facing several scientific and engineering challenges
    - Software stack
    - Data management
    - Control algorithms
    - Test environments and real-time system testing

Past



Present

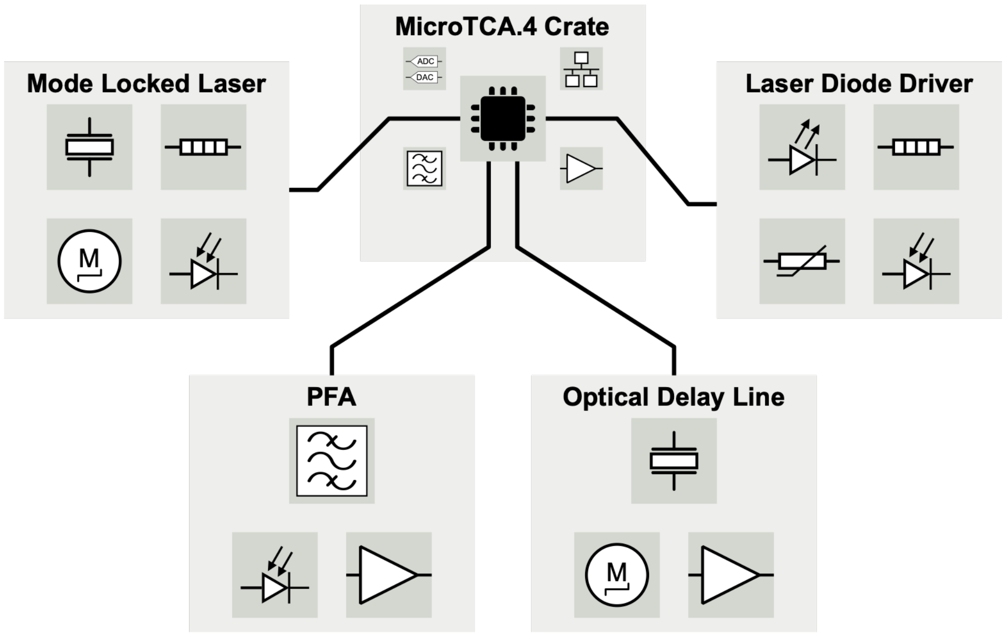
Future

European XFEL: Optical synchronization system

Data mining and data analytics

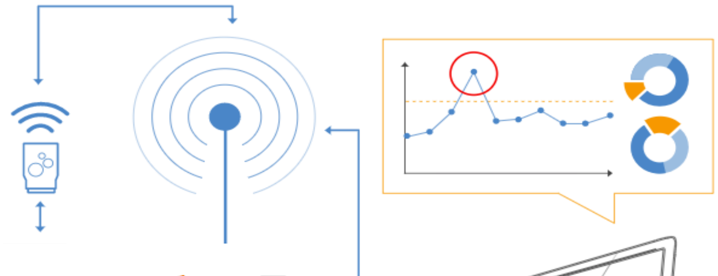
- Build a complete long-term data acquisition system for the optical synchronization system (PHD Thesis of Maximilian Schütte, MSK)
- Data scope:
  - 50’000+ data channels (configuration + monitoring),
  - In total > 150 MB/s data to data acquisition system

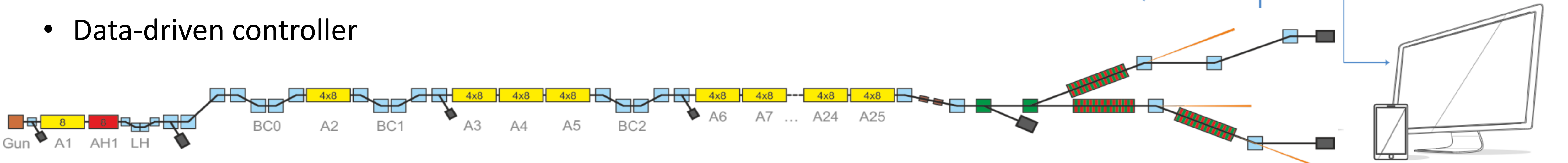
    → Data reduction necessary (to meet 100 TB/y)
  - ~ 1% of the European XFEL



Goals

- Data analysis for better system understanding (Bachelor Thesis with HAW)
- Develop predictive maintenance algorithms (PhD Thesis will start in March)
- Data-driven controller

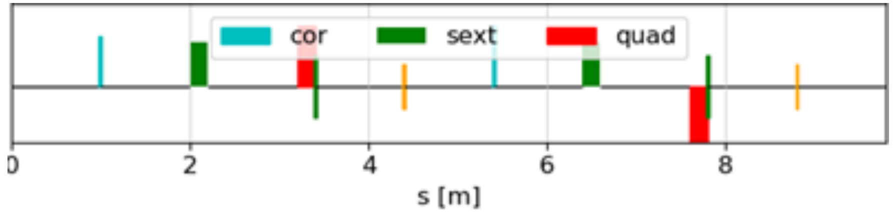


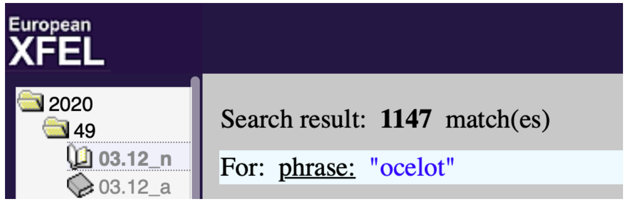


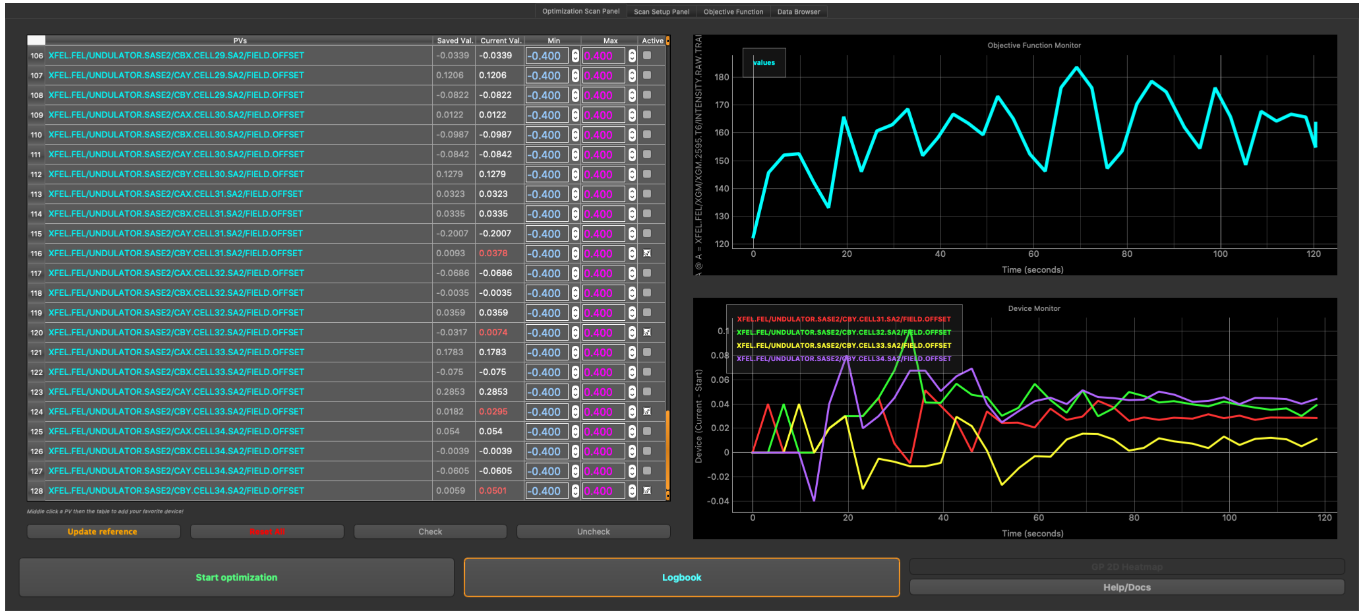
Reinforcement learning for optimization

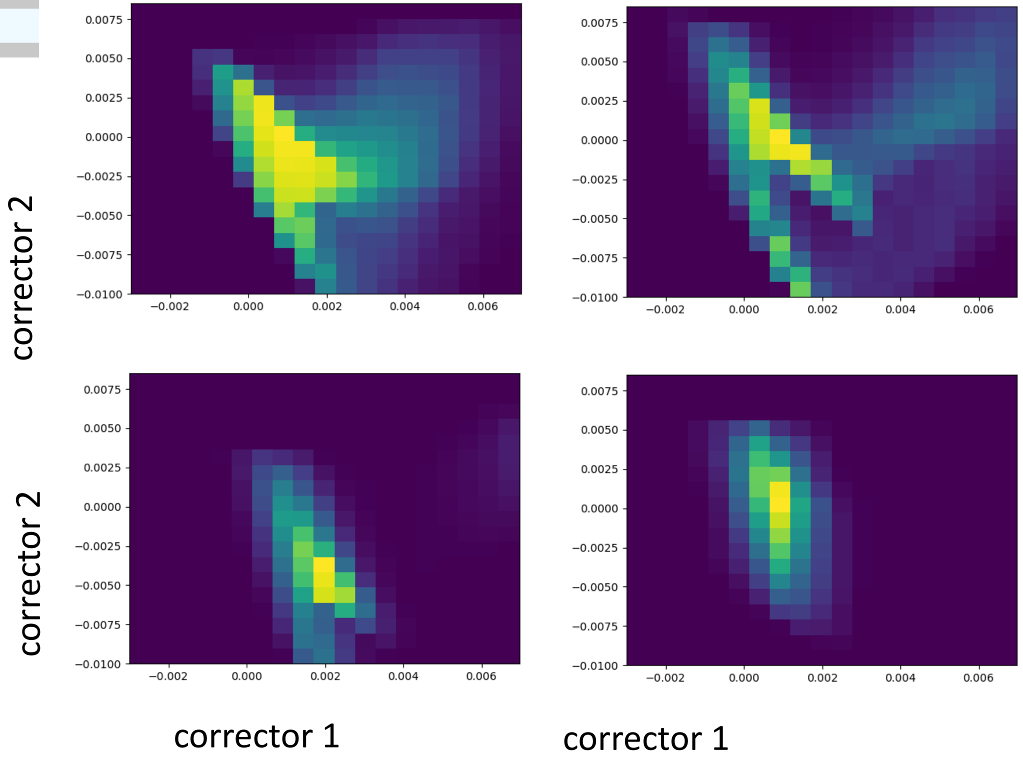
Benchmark problem: transmission through a beamline with aperture and non-linear optics

- nonlinear response
- random realization
- Toy model of accelerator tuning – based on experience of FEL tuning





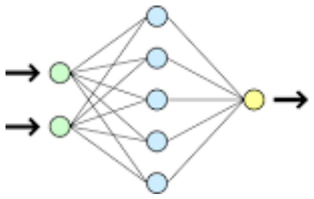




RL for control

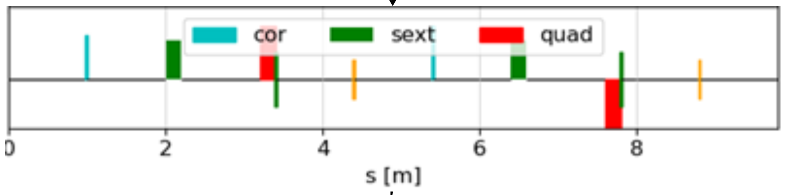
NN is trained with historical data and learns an optimal policy

Traditional RL agents

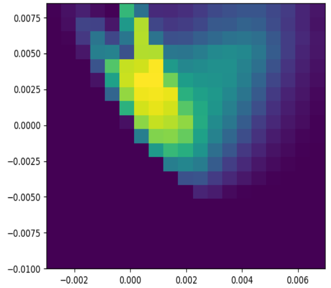


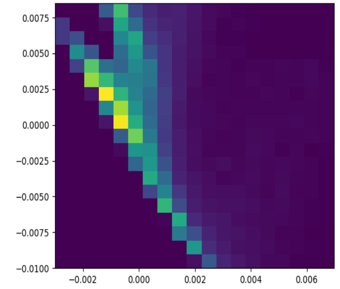
correctors

random misalignments

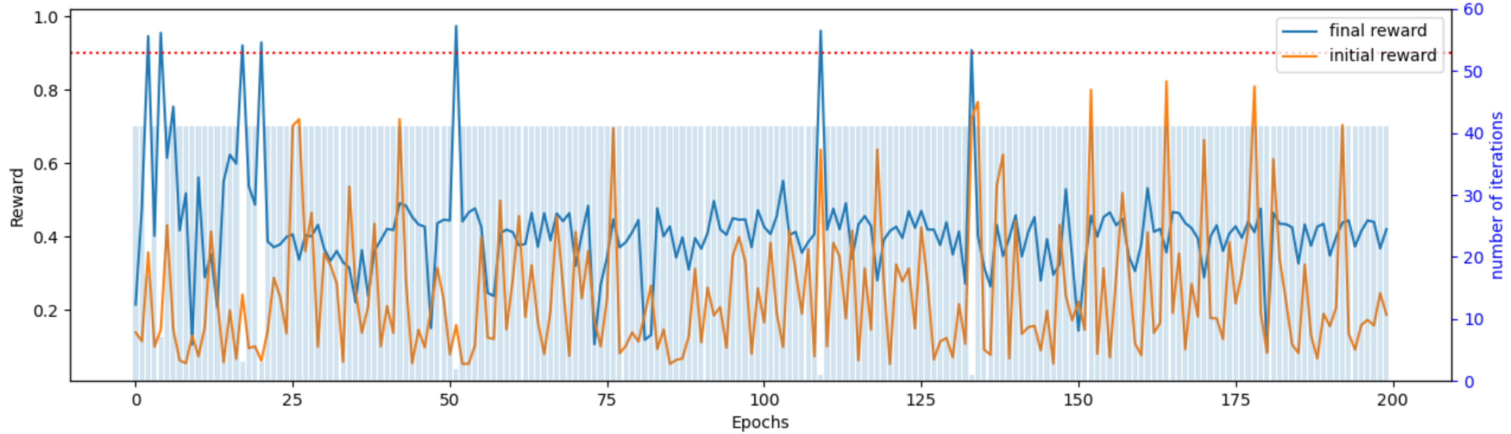


Observations (transmission rate and correctors)



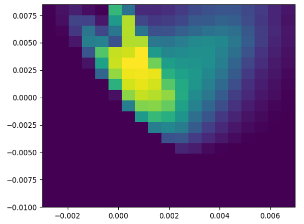


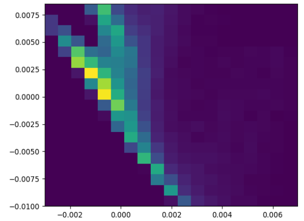
c/o A. Ivanov (MPY)

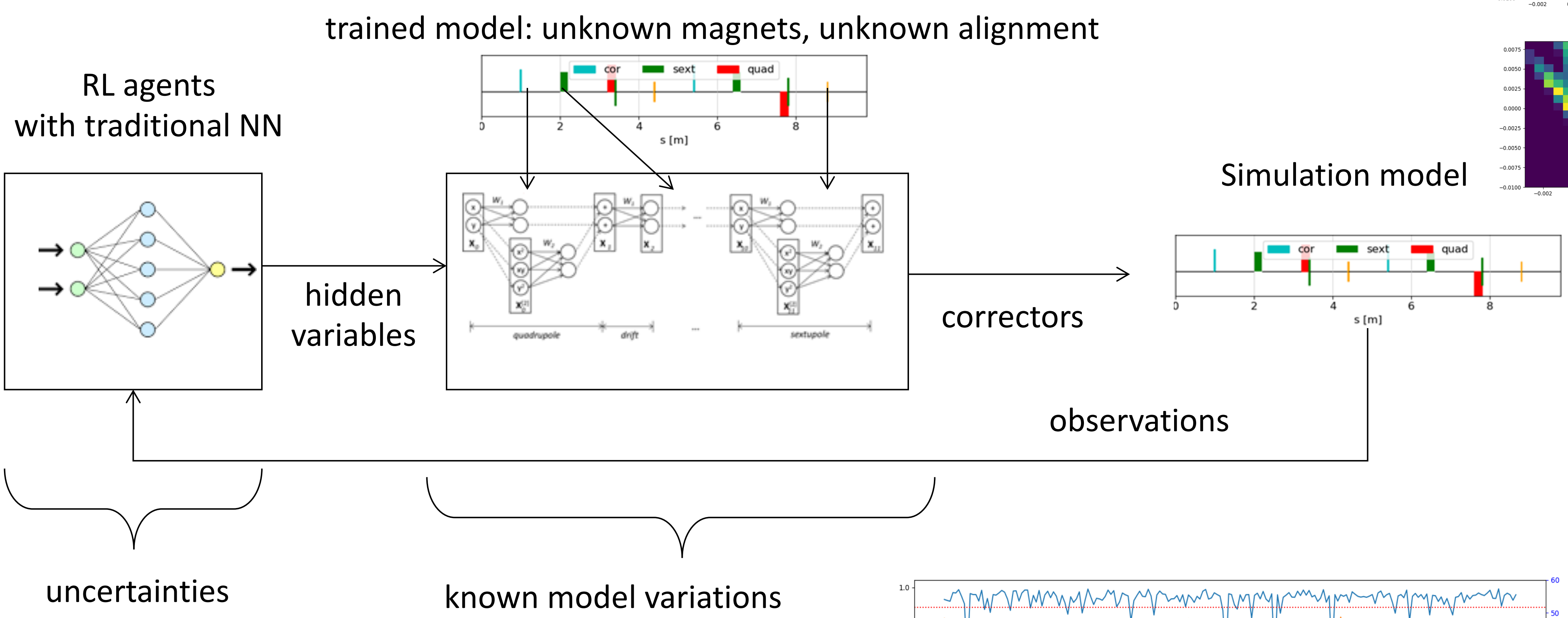


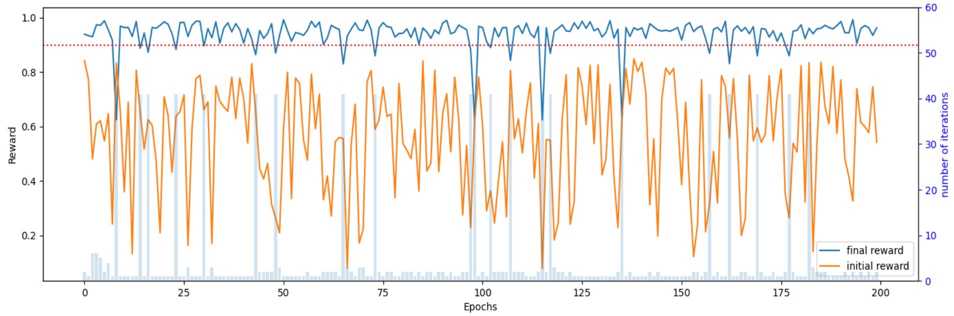
RL for control enhanced by physics-based NN

Incorporate a priory knowledge in form of trainable NN





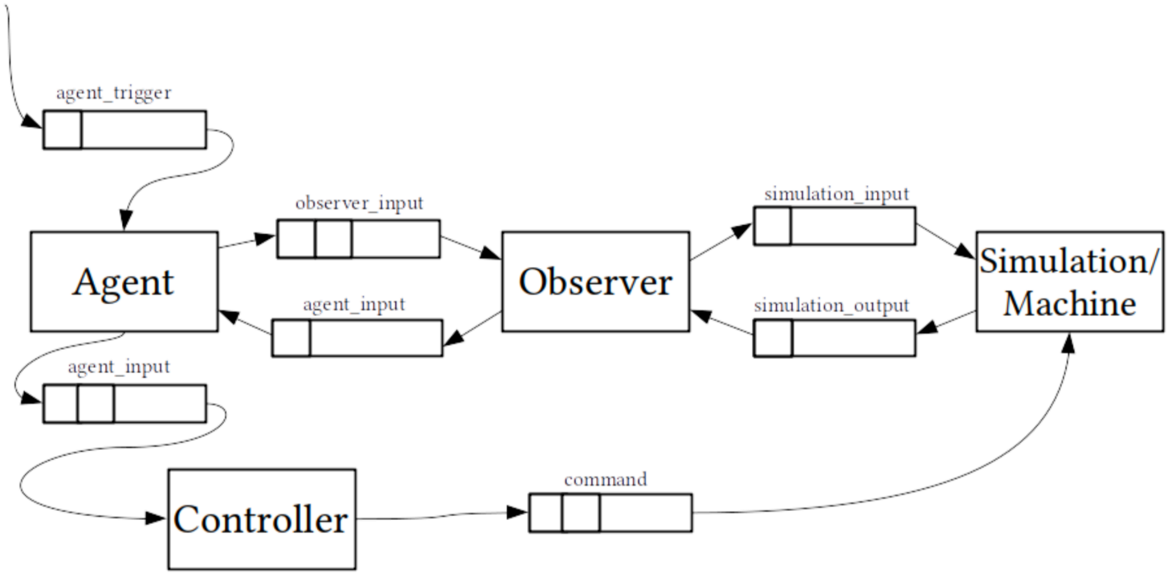




For DNN for accelerator control see Phys. Rev. Accel. Beams **23**, 074601
RL paper in preparation

Notification pipeline and gym environment

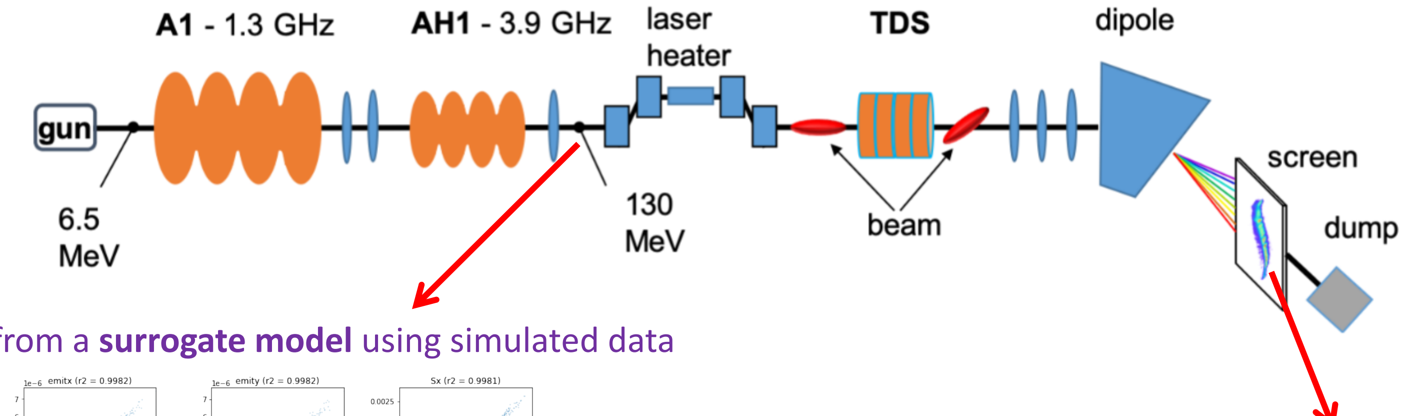
- Kafka-based notification framework
- Simulation environments
- Common interfaces for optimization and control agents



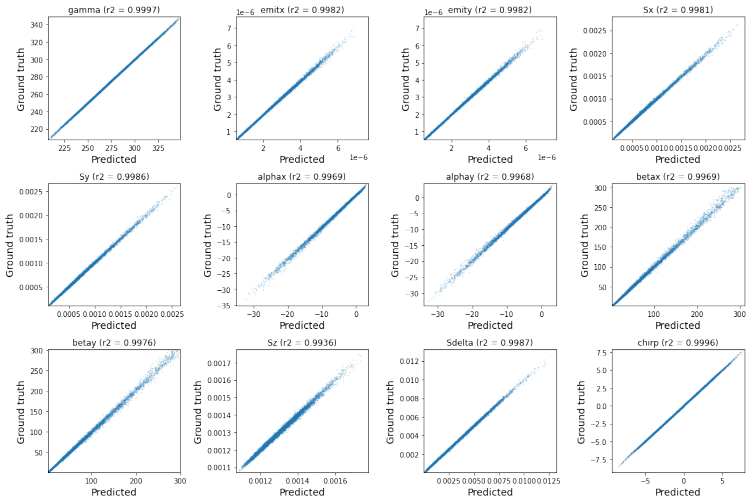
c/o M. Boese (MPY)

Multi-task learning at the injector of European XFEL (Jun Zhu / MSK)

Modeling/test environments

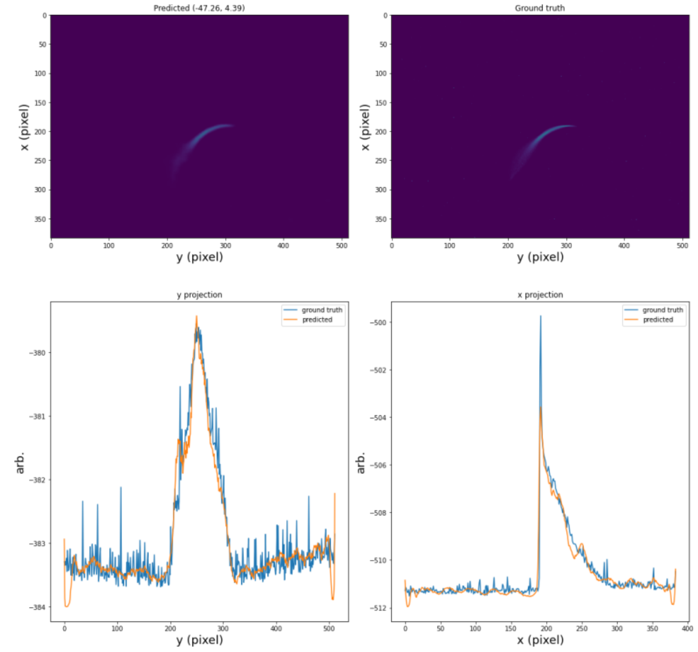


Prediction result from a **surrogate model** using simulated data



We have experimentally demonstrated using machine parameters to predict the image on a screen (**virtual diagnostic** - longitudinal phase-space of e-beam)

J. Zhu, Y. Chen, S. Tomin, et. al.



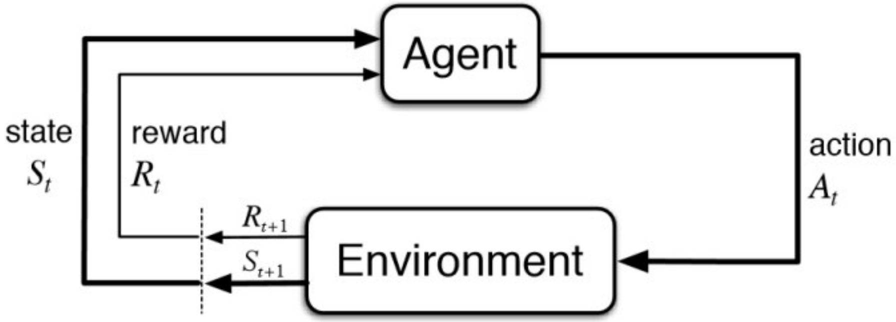
- **Surrogate model** speeds up simulation by several orders of magnitude, which can be used for online algorithm development and benchmark, starting point generation for online optimization, etc.
- **Virtual diagnostic** can be a good complement for disruptive diagnostics during operation.

tests

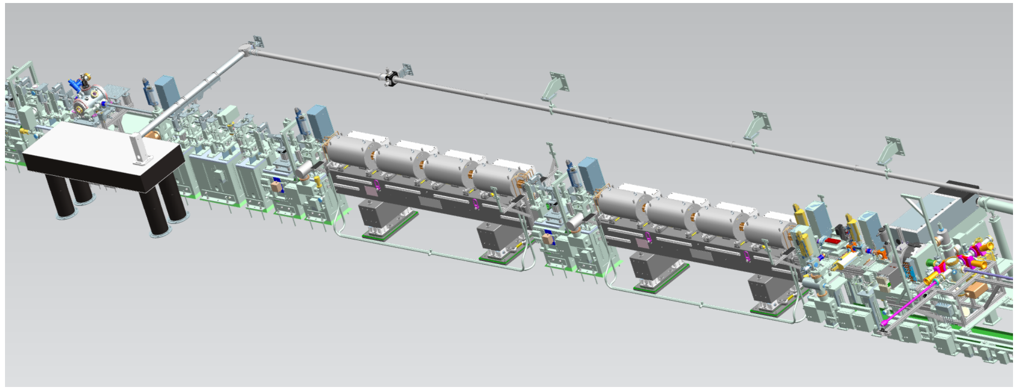
Helmholtz AI project: Autonomous Accelerator

Real-time data driven feedback control

- Helmholtz Incubator Information and Data Science (Annika Eichler, MSK)
- ARES as test case (Florian Burkart, MPY1)
- Collaboration with KIT (FLUTE)
- Starts now!

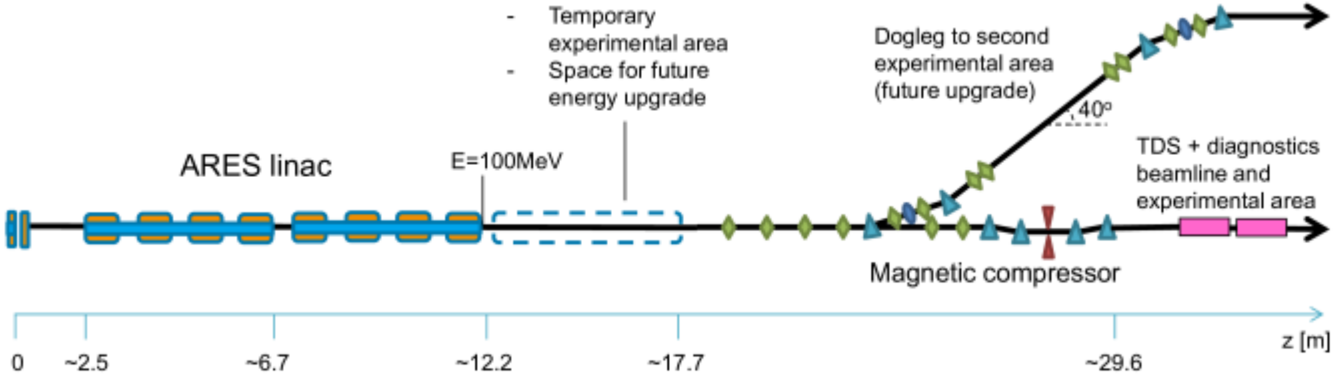


Sutton: Reinforcement Learning, an introduction



Goals

- Bring Reinforcement Learning to accelerator control
- Standardized interface (simulations + facilities)
- Proof of principle: Longitudinal phase-space control
- Next step:
  - Autonomous start up (from predefined fault)



ARES, courtesy Florian Burkhart

Towards autonomous accelerator

Key ingredients:

- Coherent effort across several M Groups
- Common and growing software stack
- Experimental programme at ARES, XFEL, and PETRA
- External collaborations