Karlsruhe Institute of Technology

Towards Automatic Tuning and Control of Accelerators

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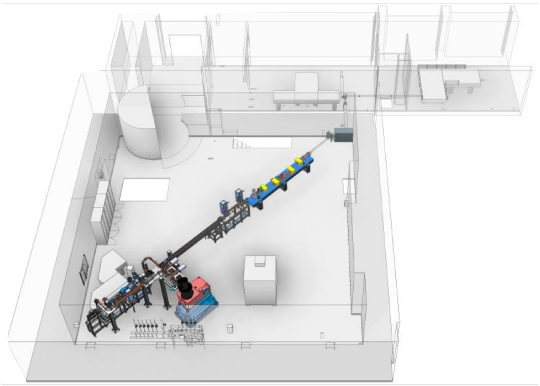

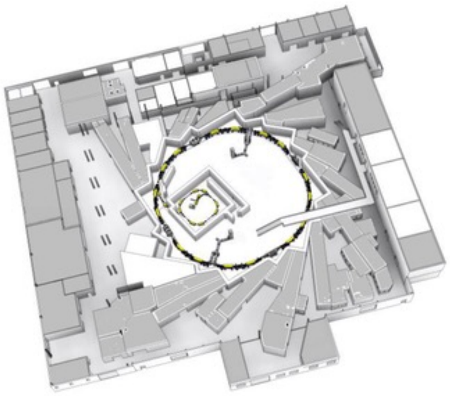

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Machine Learning Towards Autonomous Accelerator

HELMHOLTZ AI | ARTIFICIAL INTELLIGENCE COOPERATION UNIT

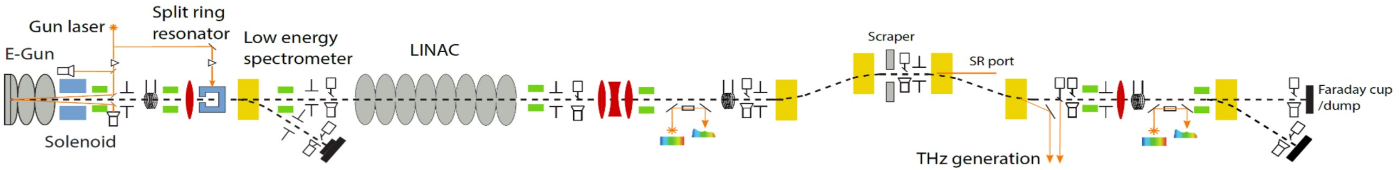
This work is funded by the Initiative and Networking Fund by the Helmholtz Association (Autonomous Accelerator, ZT-I-PF-5-6).

Far-reaching goal:
- Automatic start-up of electron linear accelerators

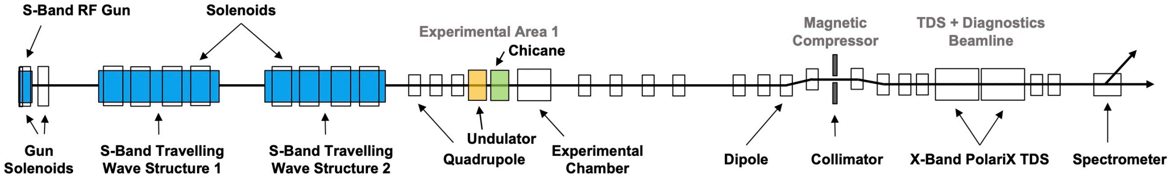
Project goals:
- Control of the bunch profile (with RL)
- Transferability between two similar facilities

	FLUTE	ARES
Final energy [MeV]	40 - 50	100 - 155
Bunch charge [pC]	1 - 3000	0.5 - 30
Bunch length [fs]	1 - 300	0.2 - 10
Pulse repetition rate [Hz]	1 - 10	10 - 50

FLUTE



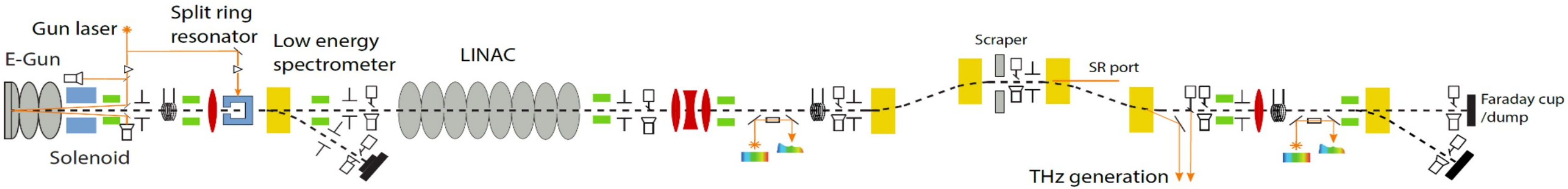
ARES



TUPAB298, IPAC21

Pulse Shaping with Spatial Light Modulators (SLM)

FLUTE is a test facility to study, tailor, and control **ultra-short electron bunches**

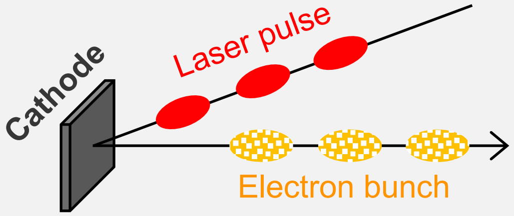


Motivation: generate broadband terahertz (THz) pulses **tailored to use cases**

Idea:

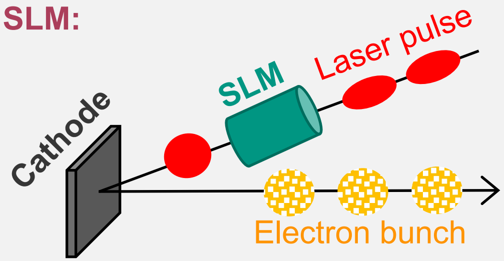
Properties of the **electron bunch** heavily dependent on the **photocathode laser**

Usual operation:



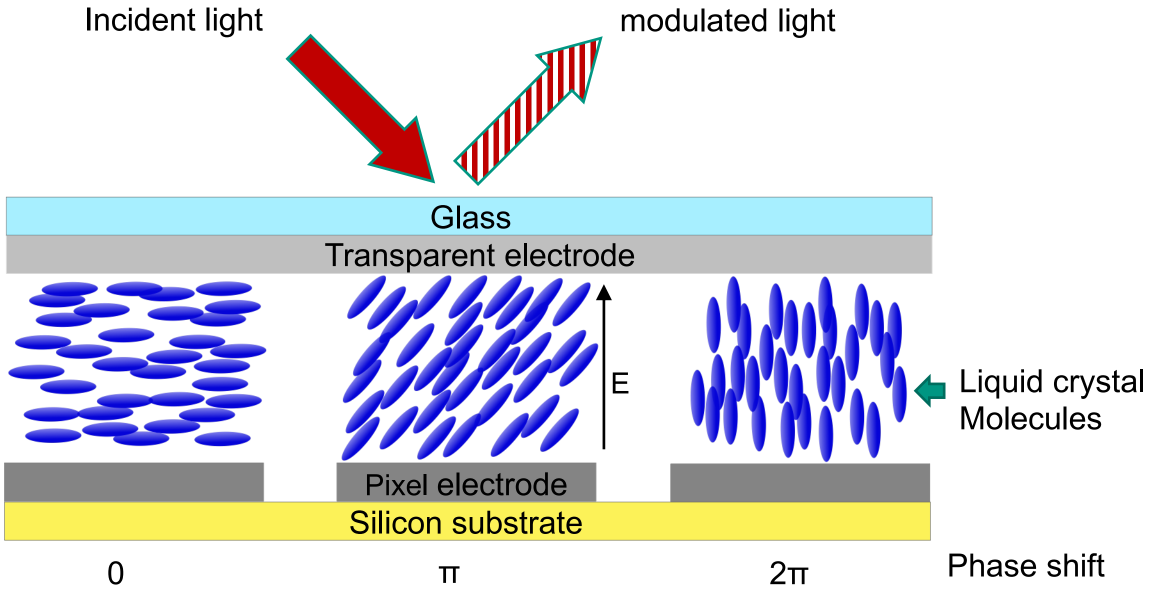
Spatial Light Modulator shapes the laser pulses and therefore the electron bunch

With SLM:



Spatial Light Modulator

- Working principle of **Liquid Crystal on Silicon** (LCoS) SLMs
- Input SLM: **phase pattern**

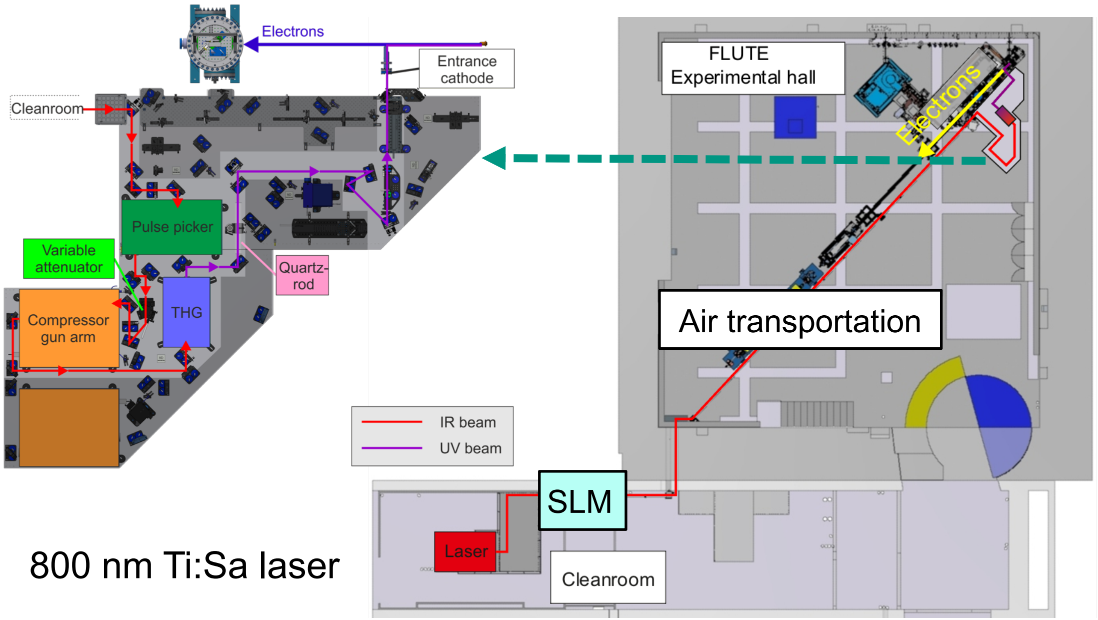


KIT-Logo generated using SLM

Courtesy: Carl Sax

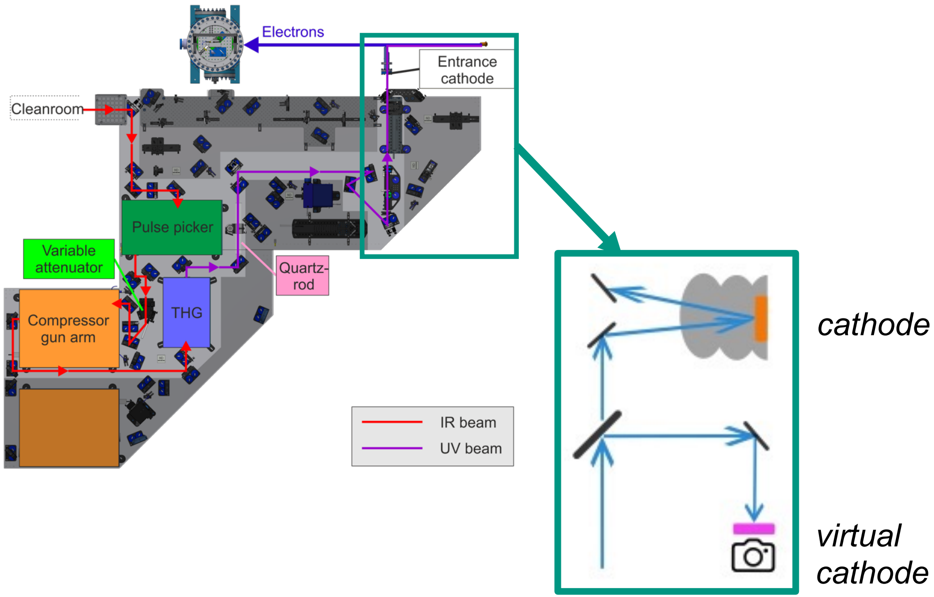
Spatial Light Modulator Control

Laser will be subjected to **nonlinear transformations** inherent to the transportation path
→ SLM modulation will be **distorted**



We propose to use Convolutional Neural Network (CNN) to **learn the distortions** in the propagation path and **compensate them**

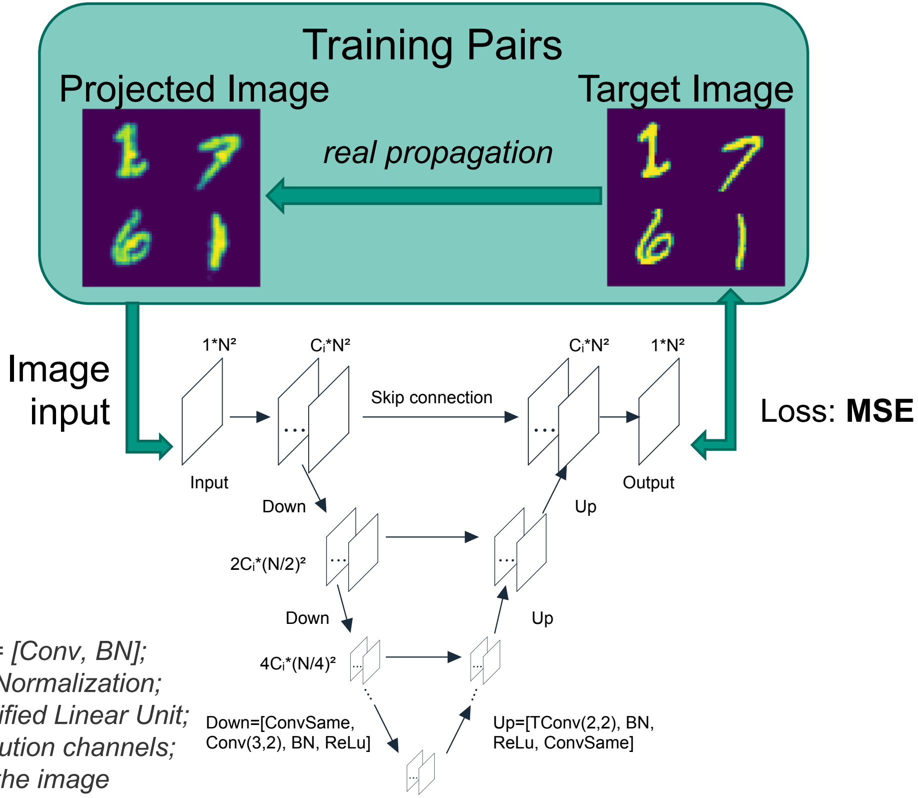
Spatial Light Modulator Control



- **Virtual cathode**
  - Laser travels through the exact same distance as real cathode
  - Direct diagnostic for laser property on the cathode
  - Can be used as feedback signal for SLM

CNN Architecture

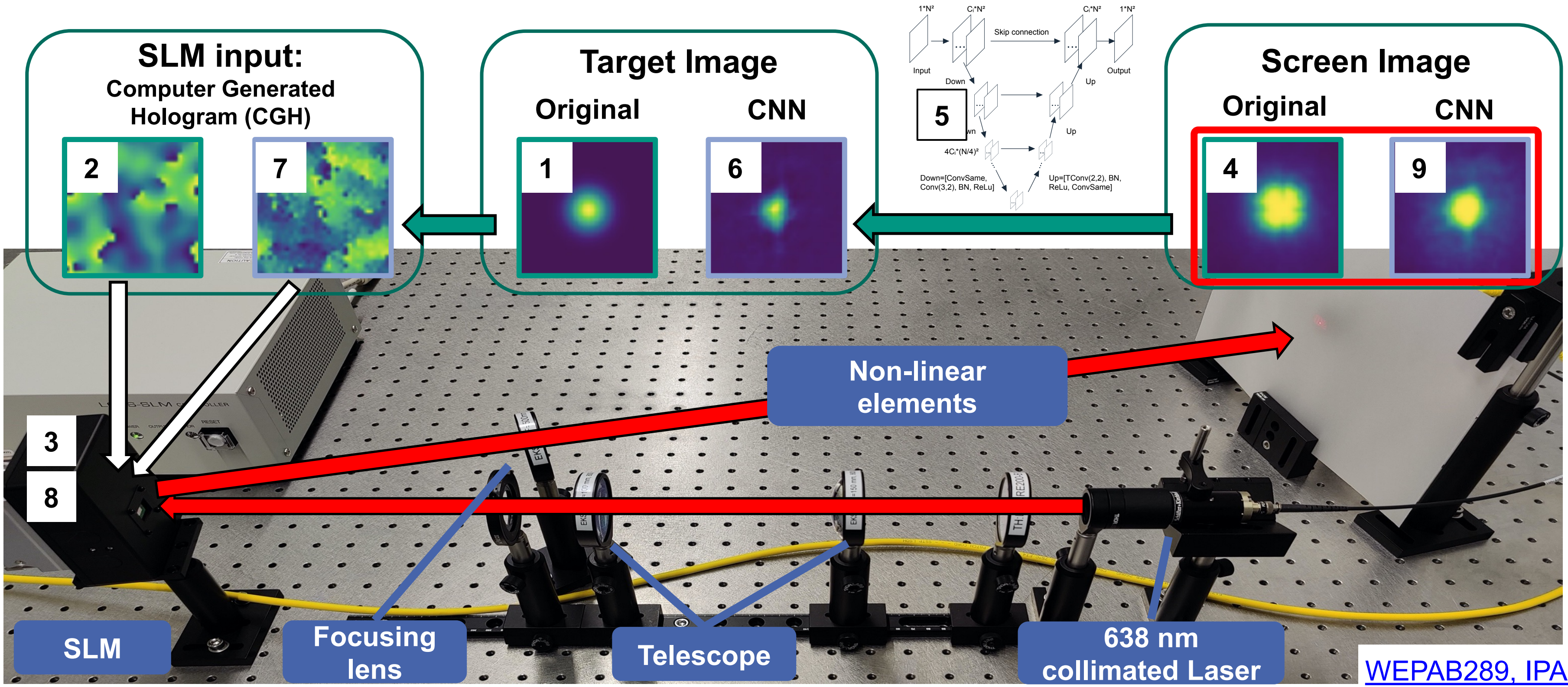
- Learning the **inverse propagation process**
- **U-Net** based structure:
  - specially for image processing
  - consecutive down- and up-sampling layers with skip-connection
- First proof of principle test
  - Training data: 10k MNIST images
  - N=32



ConvSame = [Conv, BN];
BN = Batch Normalization;
ReLu = Rectified Linear Unit;
C = # convolution channels;
N^2 = size of the image

WEPAB289, IPAC21

Transverse Laser Shaping: Test Setup

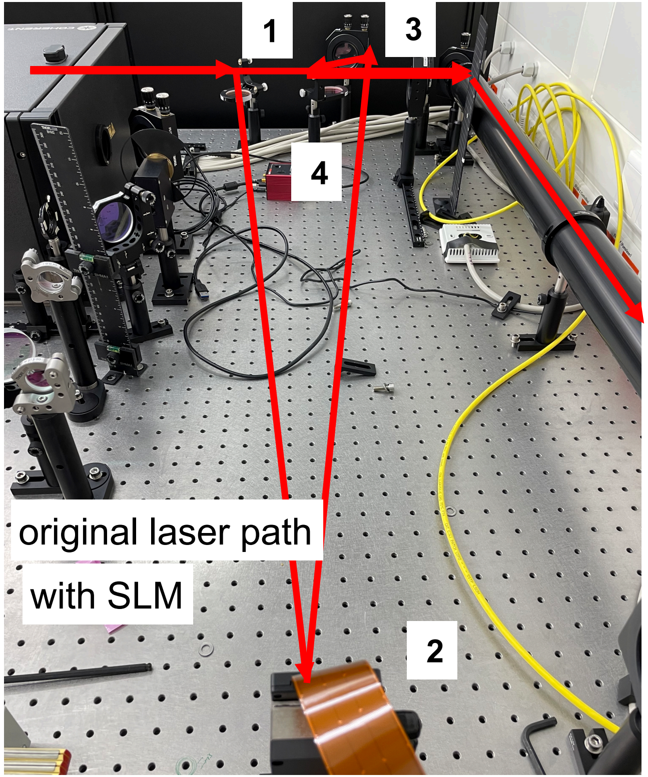


WEPAB289, IPAC21

Transverse Laser Shaping: FLUTE Laser

- **Ongoing Project**: Implement transverse modulation setup in FLUTE laser cleanroom
  - 1,4: Foldable mirrors allowing quick switch between normal or SLM operation mode
  - 2: LCoS-SLM
  - 3: Mirror

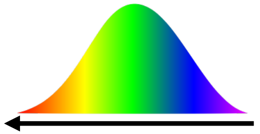
- **Next Steps**:
  - Elimination of 0-order unmodulated light using diffraction grating
  - Use virtual cathode images as feedback
  - **Generate electron bunches** with modulated laser pulse

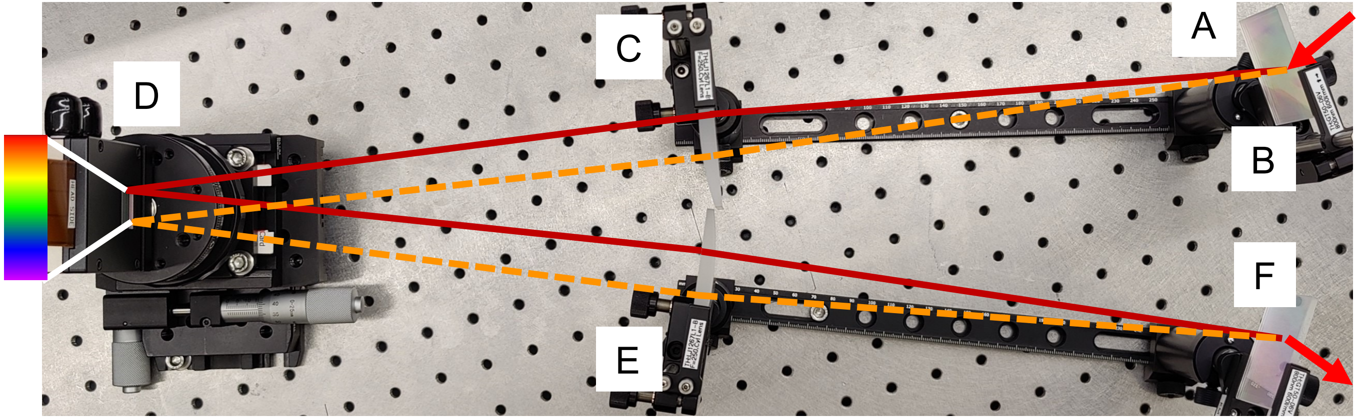


Thanks to: Matthias Nabinger
& Michael J. Nasse

Longitudinal Laser Shaping Setup

1. **Chirped laser** correlates wavelength and time
2. **Grating** disperses light, spectral components of the laser are separated spatially
3. **SLM** modulates the **femtosecond laser** in spatial and therefore in **time domain**





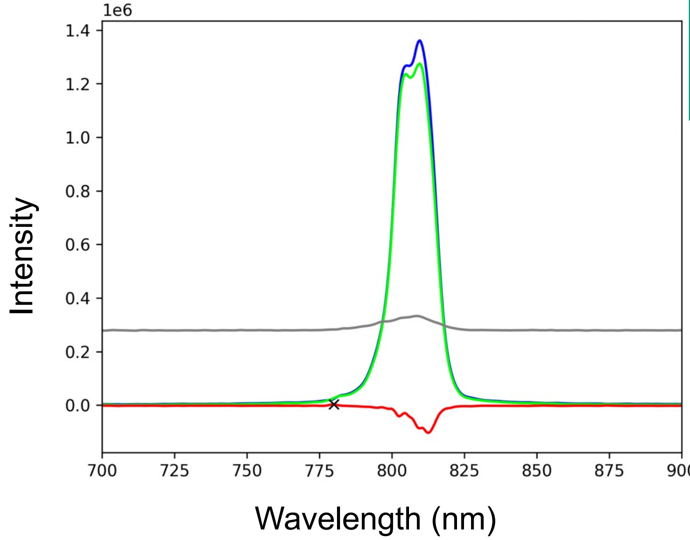
A: 750-850 nm laser
B, F: Transmission grating
C, E: Cylindrical lens
D: SLM

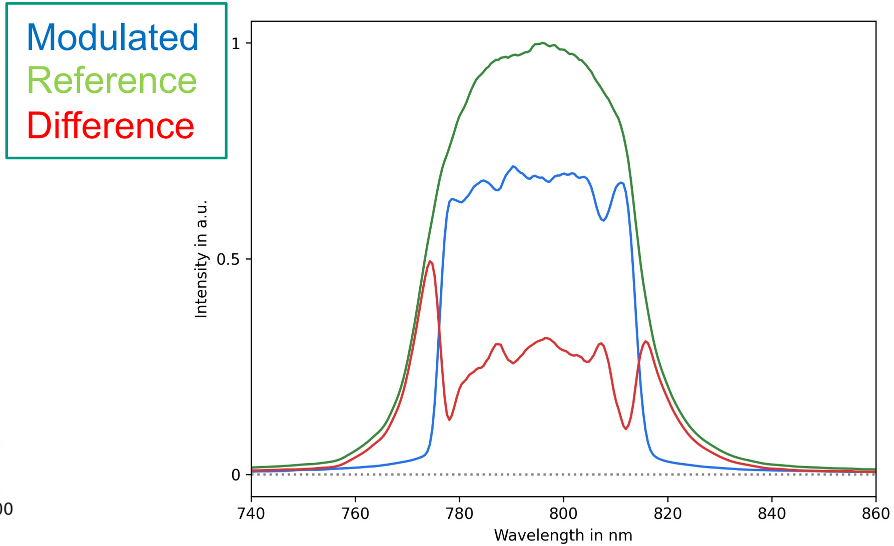
Courtesy: Carl Sax

Setup of the time domain system

Longitudinal modulation setup built in cleanroom using laser from side arm

First result of the **top-hat profile** generation





Courtesy: Carl Sax

Pulse Shaping with SLM: Roadmap

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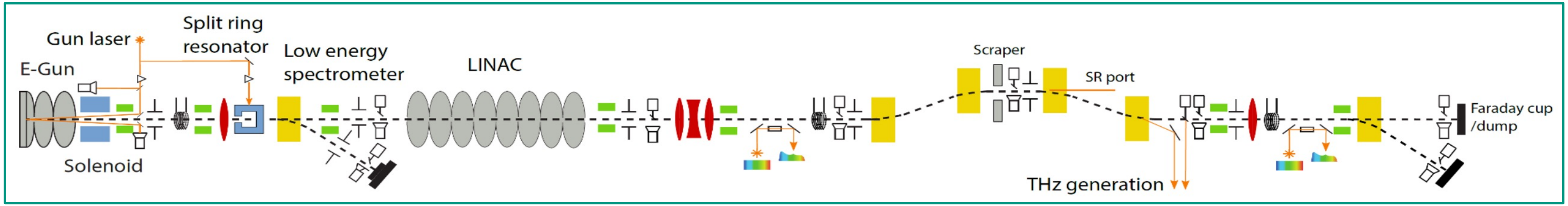
Achieved:
- Test setup with 638 nm laser

Working project:
- Feasibility study setup with 800 nm FLUTE laser; Generation of electrons with transversely modulated laser
- Longitudinal setup; Generation of different pulse profiles

Long-term Goal:
- Potential permanent setup in FLUTE experimental hall for 3D laser modulation

Reinforcement Learning Control



Motivation: generate broadband terahertz (THz) pulses **tailored to use cases**

Automatic control of the accelerator parameters required: magnet strength, gun phase & amplitude, solenoid strength...

→ **Reinforcement learning** algorithms observe the **state** of an **environment** and take **actions** to optimize the cumulative **reward**

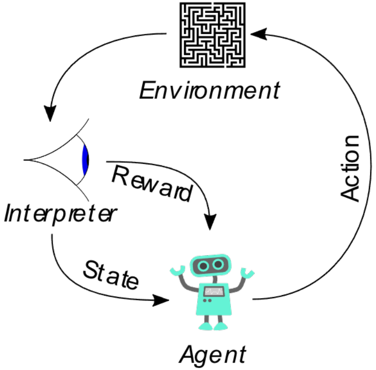
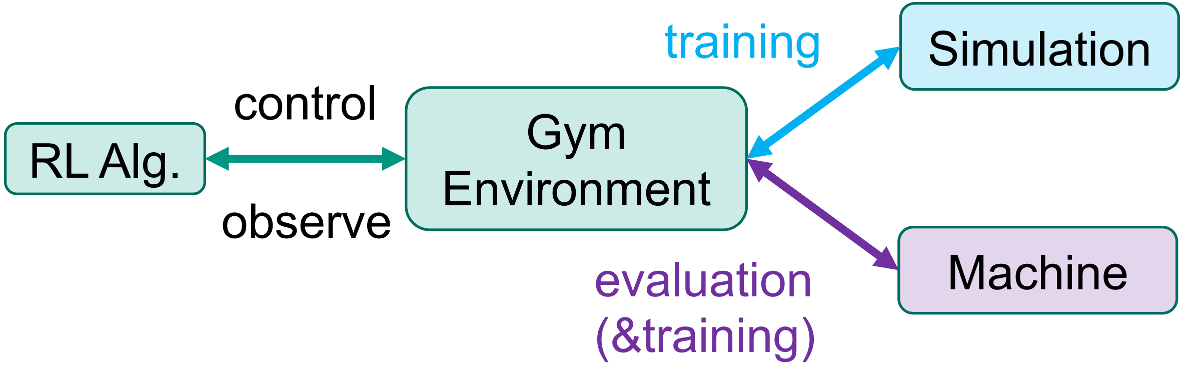


image from: wikipedia.org

Reinforcement Learning Environment

- **RL Environment**: **OpenAI Gym**, a standardized toolkit for development and evaluation of reinforcement learning algorithms

- **Simulation**: Ocelot, ASTRA...
- **Machine Interface**: pydoocs (ARES), pyepics (FLUTE)...




Ocelot

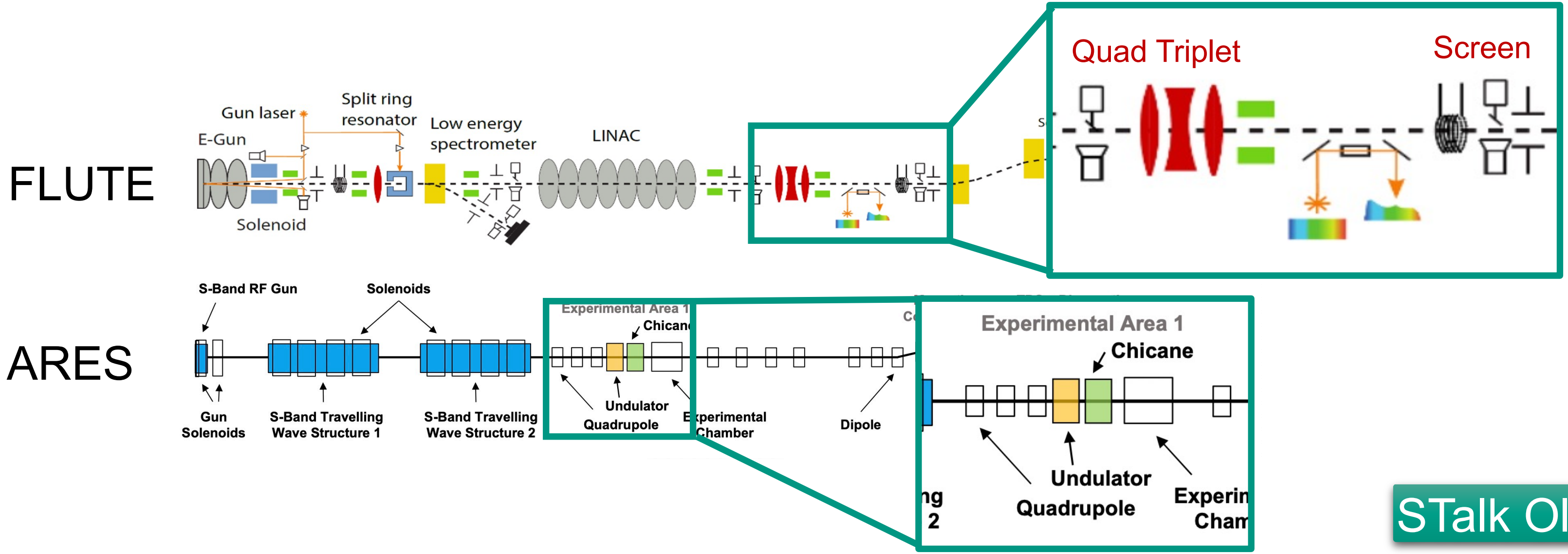
ASTRA

DOOCS

EPICS

Test Environment: Quadrupole Focusing

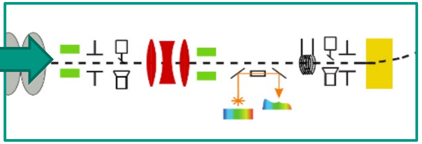
- First RL test on realistic lattice: **Quadrupole triplet focusing**
- Similar structure in both facilities



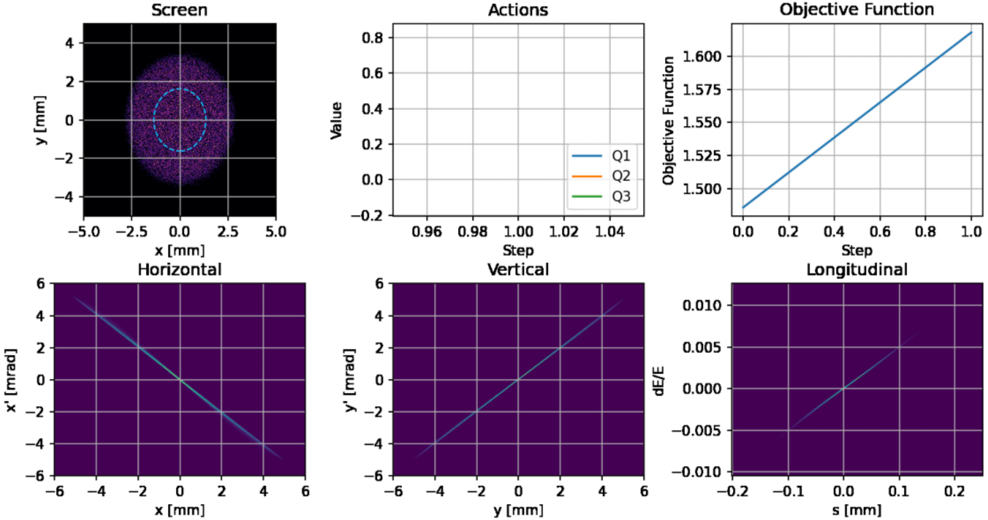
STalk Oliver Stein

Test Environment: Quadrupole Focusing

ASTRA beam distribution



OCELOT simulation



Actuators: k-values of Q1, Q2, Q3
Observation: $[\sigma_x,\ \sigma_y\ , Q_1.k, Q_2.k, Q_3.k]$

Reward: $-\max(\sigma_x,\ \sigma_y)$
→ Minimize both x- and y-beam size

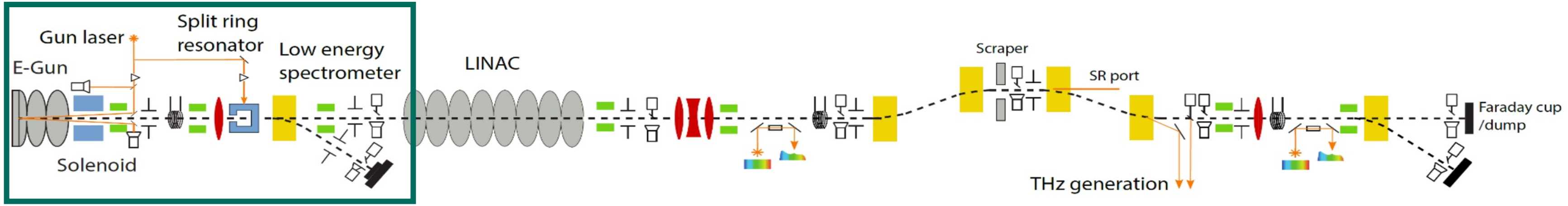
First result using **Proximal Policy Optimization** (PPO) agent

- Widely used model-free on-policy Actor-Critic algorithm
  - + easy to use
  - - low sample efficiency
- Training on GPU cluster
  - 300k steps ~ 22h
- Tensorized simulation model (w/o space charge) speeds up pre-training

Thanks to: Jan Kaiser & Oliver Stein

Reinforcement Learning at FLUTE: Next Steps

- Test different RL algorithms; Reward shaping...
- Benchmark against other optimization algorithms
- Implement gym environment for low energy section
  - Actuators: Gun phase, amplitude, solenoid, ...
  - Objectives: $\mathrm{E},\ \sigma_E,\ \sigma_x,\ \sigma_y$
  - Use ASTRA as simulation backend
  - All devices are installed and working → measurement possible

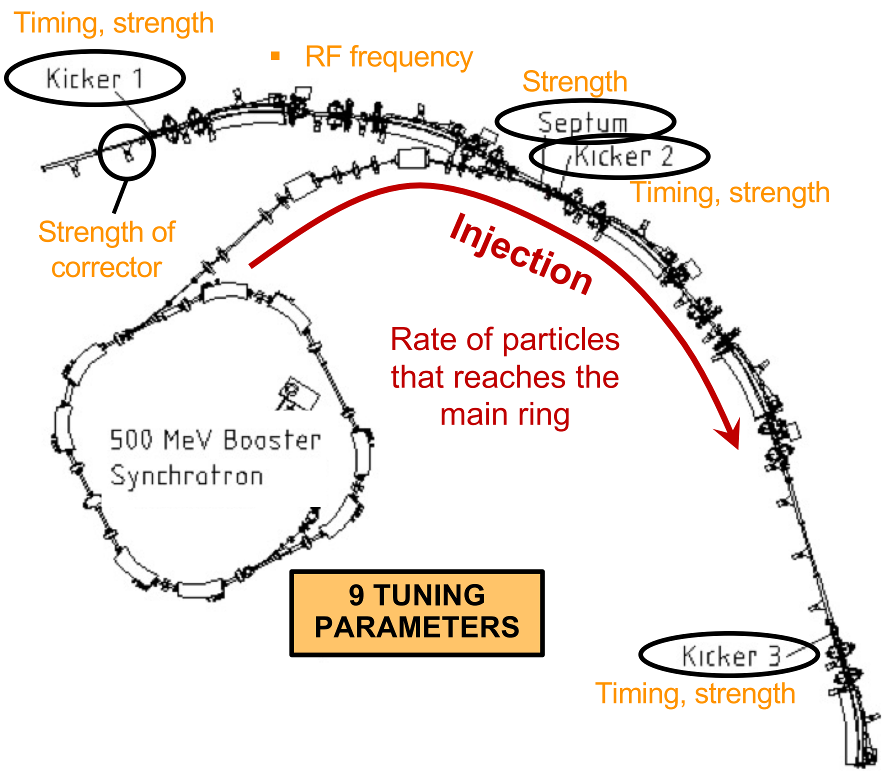


Bayesian Optimization at KARA

Goal: Improve the injection rate from the booster to the storage ring KARA automatically

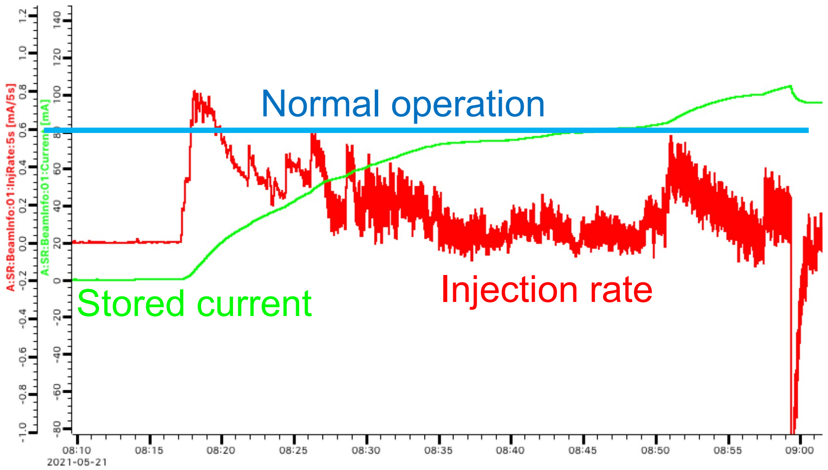
Manual trial-and-error
- Time consuming
- Easily stuck in local optima

Tool: **Bayesian optimization**
- Global optimization
- Fast tuning
- Implemented in other facilities



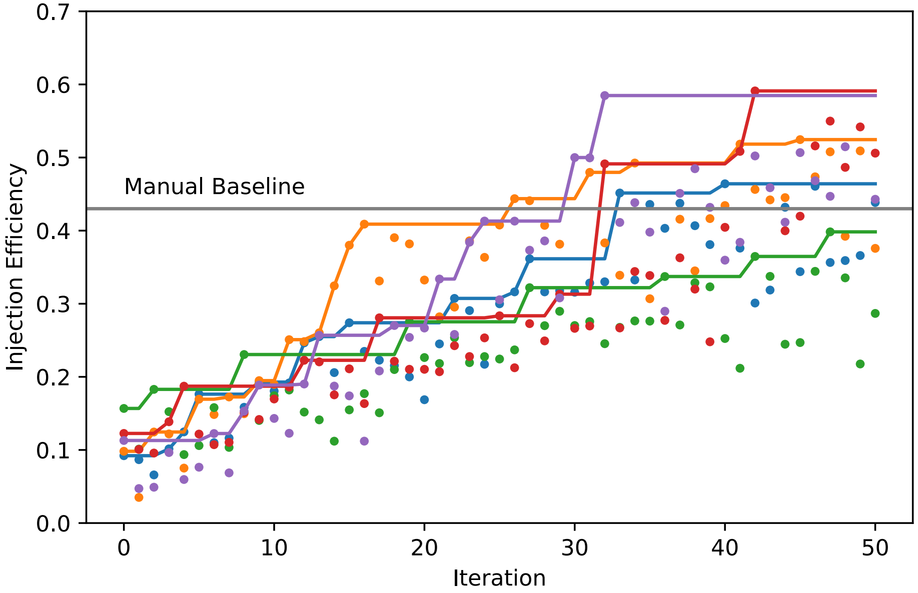
Bayesian Optimization for commissioning

- New **power supplies** for **kicker** and **septa** magnets installed at KARA
- Commissioning needed to find **new magnet settings**



Opportunity to use our previously developed **Bayesian Optimization** algorithm to improve the injection rate

Bayesian Optimization for commissioning



- BO packaged as **singularity container** in control room
  - Runtime Jupyter notebook available
  - Easy to use for operators
- Changing config file to easily update/change machine interface
- Manual baseline outperformed in most cases
  - 5 runs with UCB acquisition
  - 6 input parameters: RF frequency, MCH01, Septum, Kicker1-3 strength

Thank you for your attention!

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