Machine Learning in Accelerator Physics

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1 Overview

1. Auralee Edelen et al., *Opportunities in Machine Learning for Particle Accelerators*, arXiv (2018). DOI: 10.48550/arXiv.1811.03172

2 Optimization and Tuning Task

achieve desired beam properties or states by tuning machine parameters

2.1 Bayesian Optimization

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3. C. Xu et al, *Optimization Studies of Simulated THz Radiation at FLUTE*, Proc. 13th International Particle Accelerator Conference, Bangkok, Thailand (2022). DOI: 10.18429/JACoW-IPAC2022-WEPOMS023
4. Ryan Roussel, Adi Hanuka, and Auralee Edelen, *Multiobjective Bayesian optimization for online accelerator tuning*, Phys. Rev. Accel. Beams 24 (2021). DOI: 10.1103/PhysRevAccelBeams.24.062801
5. S. Jalas et al, *Bayesian Optimization of a Laser-Plasma Accelerator*, Phys. Rev. Let. 126 (2021). DOI: 10.1103/PhysRevLett.126.104801
6. R. Roussel et al, *Turn-key constrained parameter space exploration for particle accelerators using Bayesian active learning*, nature communications 12 (2021). DOI: 10.1038/s41467-021-25757-3
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2.2 ML-based Tuning

1. Alexander Scheinker, *Adaptive Machine Learning for Robust Diagnostics and Control of Time-Varying Particle Accelerator Components and Beams*, Information 12 (2021). DOI: 10.3390/info12040161
2. Alexander Scheinker et al., *Online multi-objective particle accelerator optimization of the AWAKE electron beam line for simultaneous emittance and orbit control*, AIP advances 10 (2020). DOI: 10.1063/5.0003423
3. M. D'Andrea et al., *Prospects to Apply Machine Learning to Optimize the Operation of the Crystal Collimation System at the LHC*, Proc. 13th International Particle Accelerator Conference, pp. 1362–1365 (2022). DOI: 10.18429/JACoW-IPAC2022-TUPOTK061
4. S. C. Leemann et al., *Demonstration of Machine Learning-Based Model-Independent Stabilization of Source Properties in Synchrotron Light Sources*, Phys. Rev. Lett. 123 (2019). DOI: 10.1103/PhysRevLett.123.194801
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2.2.1 Orbit

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3 Reinforcement Learning

Using RL to control the state of the beam in real time in a dynamically changing environment

1. Jan Kaiser, Oliver Stein, and Annika Eichler, *Learning-based Optimisation of Particle Accelerators Under Partial Observability Without Real-World Training*, Proceedings of the 39th International Conference on Machine Learning, Baltimore, US, pp. 10575–10585 (2022). URL: `https://proceedings.mlr.press/v162/kaiser22a.html`

2. V. Kain et al., *Test of Machine Learning at the CERN LINAC4*, Proc. 64th ICFA ABDW on High-Intensity and High-Brightness Hadron Beams, Batavia, USA, pp. 181–185 (2022). DOI: `10.18429/JACoW-HB2021-TUEC4`

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10. Verena Kain et al., *Sample-efficient reinforcement learning for CERN accelerator control*, Phys. Rev. Accel. Beams 23 (2020). DOI: `10.1103/PhysRevAccelBeams.23.124801`

11. T. Boltz et al., *Feedback Design for Control of the Micro-Bunching Instability based on Reinforcement Learning*, Proc. 10th International Particle Accelerator Conference, Melbourne, Australia, pp. 104–107 (2019). DOI: `doi:10.18429/JACoW-IPAC2019-MOPGW017`

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4 Prediction Task

predict beam properties based on current accelerator parameters

4.1 Surrogate Model, Virtual Diagnostics

1. Andreas Adelmann, *On Nonintrusive Uncertainty Quantification and Surrogate Model Construction in Particle Accelerator Modeling*, SIAM/ASA Journal on Uncertainty Quantification 7 (2019). DOI: `10.1137/16M1061928`

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4. Owen Convery et al., *Uncertainty quantification for virtual diagnostic of particle accelerators*, Phys. Rev. Accel. Beams 24 (2021). DOI: `10.1103/PhysRevAccelBeams.24.074602`

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4.2 Anomaly Detection, Forecasting

detect outliers and anomalies in archive data or during operation

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6. Sichen Li et al., *A Novel Approach for Classification and Forecasting of Time Series in Particle Accelerators*, Information 12 (2021). DOI: `10.3390/info12030121`

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5 Misc

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