pyAT developments at Solaris, ML anomaly detection and measurement scripts porting

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Agenda

- Introduction of the SOLARIS light source
- pyAT implementation at SOLARIS, lifetime simulation, realistic k-factors from LOCO fits
- Anomaly detection with ML, forecasting, detecting beam distortion, ground disturbance and BPM maintenance
- Measurement scripts porting to python
- Conclusions



The Solaris accelerator facility – electron storage ring

Energy	1.5 GeV
Max. current	500 mA
Circumference	96 m
Main RF frequency	99,93 MHz
Max. number of circulating bunches	32
Horizontal emittance (without insertion devices)	6 nm rad
Electron beam size (straight section center) σ_{x} , σ_{y}	184 μm, 13 μm
Electron beam size (dipole center) σ _x , σ _y	44 μm, 30 μm
Max. number of insertion devices	10
Momentum compaction	3.055 x 10 ^{−3}
Total lifetime of electrons	13 h

ARIS

One DBA cell – 12 in the entire ring

Beam correction and diagnostic:

-36 Libera Brilliance + (connected in 12 chassis) connected to 36 BPMs (one BPM in X,Y plane)

-We use GDX module for fast orbit feedback

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pyAT implementation at SOLARIS

- Simulations of the storage ring
- Active cavities included
- Realistic k factors for dipoles and SQF-in/out included
- Tauchek time simulation vs measurement

Simulation of SOLARIS storage ring, no IDs, no Landau cavity.

Setup as follows: Frac. tunes (6D motion): [0.24074793 0.17832712 0.0019657] Energy: 1.500000e+09 eV Energy loss / turn: 1.172449e+05 eV Mode emittances: [6.12394576e-09 6.80792546e-36 1.33319094e-05] Damping partition numbers: [1.46656042 0.99999951 1.53344006] Damping times: [0.00566874 0.00831356 0.00542151] s Energy spread: 0.000750828 Bunch length: 0.0177564 m Cavities voltage: 397200.0 V Synchrotron phase: 2.84195 rd Synchrotron frequency: 6050.16 Hz

Tauschek 32 bunches sim: 26.4 (300mA), 1000 turns Tauschek 32 bunches meas: 23.1 (300mA) Tauschek 29 bunches meas: 26.6 (300mA)

RF setup. 99.92809621818222 MHz Radiation off 98.4918938031579 MHz Radiation on





pyAT implementation at SOLARIS

- LOCO fits were used to estimate the SQFi/o horizontal focusing field strength (k)
- The quad element for the dipoles (vertical focusing) was also included in the simulation
- Beta beat calculations are overlapped with the ones coming from LOCO measurements





The problems

- Anomaly detection package for "on the fly" diagnostics (RF Cavity problem, mechanical movement)
- Undulator correction table generation
- Response matrix forecasting

The possible "solution"



Fast deployment

- <u>Engineering</u> non-scientific approach (plug & play)
- Lots of ready to use easy packages
- In the future one can switch to <u>Theano</u> for custom neuron design, <u>possible publication</u>



Solutions for anomaly detection

Key features:

✓ Multi class

- ✓ Simple architecture easy tune
- ✓ Fast, utilize many cores on CPU
- ✓ Low memory consumption
- ✓ n- dimensional input/output

Collaborative effort between: A. Wawrzyniak, M. Mleczko, M. Żurek, J. Wiechecki, M. Piszak, J. Biernat A Gradient Boosting Decision Trees Structure



https://doi.org/10.1007/s00170-020-06078-z

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Acquisition system:

- Direct signal acquisition system from the BPMs
- 10 kHz data collection rate (one sample is 0.1 ms) for each BPM (72 observables)
- FFT and PDF calculation for a fixed window of time for each monitor
- Two scenarios considered: RF cavity 1 and cavity 2 power drop and ground disturbance

X,Y position readout FFT distribution for different operation days, time window is 1 minute- OPR acts as a **TRAINING** set and OPR 1 acts as **TESTING**





Probability densities function for X and Y position normalized to 1. Different scenario included, 1 minute time window.



XGBoost tree configuration:

- Number estimators = 600
- Learning rate = 0.01
- Max depth = 10
- Objective = binary:logistic
- Verification based on standard ROC curve





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- Similar test but the data for prediction comes from a **disturbance** from **Cavity 1**
- The beam current is reduced to 200 mA
- Tests of BPM wise accuracy



10⁵ 104 disturbance form Cavity 1 103 Num 102 10¹ 10⁰ 0.0 0.2 0.4 0.8 1.0 Score 105 Normal operation 104 10^{3} 10² 101 10⁰ 0.0 0.2 0.8 0.4 0.6 1.0 Score www.synchrotron.pl

200 ms chunk



A glimpse into the test of ground disturbance detection and the influence of it on the beam position. Prediction done on a normal operation day with measurements and work on beam lines





- Bayesian neural network used for forecasting Undulator corrector current using Markov chain Monte Carlo for prior weight generation (100 bin – low precision due to PC computing power constrains)
- 2 years of previous operation used for training

$$P(A|B) = rac{P(B|A)P(A)}{P(B)}$$





$$V=\{v=(v_1,\ldots v_d)\in \{0,1\}^d: \sum_{i=1}^d v_iw_i\leqslant B\}$$

Bayes, T. 1764. "An Essay Toward Solving a Problem in the Doctrine of Chances", *Philosophical Transactions of the Royal Society of London* **53**, 370-418.

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- -0.2 -0.4 -0.6 40000 50000 +1.6782e9 14
- Anomaly detection based on the trend estimation
- 5 sigma detection threshold (Green band)
- Useful for on-line BPM diagnostic, removing malfunctioning units on the fly
- Similar can be done with PCA

Stopka



Measurement Scripts Porting

- Development of pyML, based on available MML scripts
- Simplified code structure and function dependencies
- Focus on preserving the original functionality, while improving accessibility and performance





Measurement Scripts Porting



Dispersion function





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Conclusions

- We are moving towards fast solutions based on ML for beam diagnostics, corrections including effects coming from insertion devices
- At first, we will deploy algorithms based on TF and Keras to move to testing online as soon as possible
- In the future we plan to make a custom network design based on Theano
- Developments of pyML will continue

Thank you!



backup



Functional code form Solaris and past experiments

Long Short-Term Memory networks – usually just called "LSTMs" – are a special kind of RNN, capable of learning long-term dependencies.

Key features:

- ✓ learning memory
- ✓Non- sequential
- ✓ Fast, utilize many cores on a GPU
- ✓ Low memory consumption compared to BSTS
- ✓n- dimensional input/output



The repeating module in an LSTM contains four interacting layers.



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ALS-U

Constraints for ALS-U lattice optimization.

Natural emittance	$\epsilon_0 < 155 \mathrm{pm rad}$
Maximum beta	$\beta_{x,y} < 30 \mathrm{m}$
Maximum dispersion	$\eta_x < 15 \mathrm{cm}$
Fractional tunes	$0.1 < v_{x,y} < 0.4$
Dispersion at center of straight	$ \eta_x^* < 1 \mathrm{mm}$
Beta at center of straight	$1 \mathrm{m} < \beta^*_{x,v} < 5 \mathrm{m}$
Beta in central arc bends (B3)	$\beta_{x,y}^{B3} < 4 \mathrm{m}$
Fractional tune difference	$ v_x - v_y < 0.01$
Chromatic sextupole strength (SF, SD)	$b_2 < 900 { m m}^{-3}$

