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MACHINE LEARNING ON BEAM LIFETIME AND TOP-UP EFFICIENCY*

Yipeng Sun†, ANL, Argonne, IL, USA

Abstract

Both unsupervised and supervised machine learning techniques are employed for automatic clustering, modeling and prediction of Advanced Photon Source (APS) storage ring beam lifetime and top-up efficiency archived in operations. The naive Bayes classifier algorithm is developed and combined with k-means clustering to improve accuracy, where the unsupervised clustering of APS beam lifetime and top-up efficiency is consistent with either true label from data archive or Gaussian kernel density estimation. Artificial neural network algorithms have been developed, and employed for training and modelling the arbitrary relations of beam lifetime and top-up efficiency on many observable parameters. The predictions from artificial neural network reasonably agree with the APS operation data.

UNSUPERVISED CLUSTERING OF BEAM LIFETIME AND TOP-UP EFFICIENCY

The Advanced Photon Source storage ring light source is an operating third generation synchrotron light source which has a circumference of 1104 meters and emittance of 3 nm [1]. For storage ring based synchrotron light source, beam lifetime and top-up efficiency are two critical performance indicators. It may be helpful on understanding and improving the storage ring performance by employing machine learning techniques to analyze the APS operation data.

K-means clustering is usually employed to group unlabeled samples into different classes, where samples in the same cluster may share similar features and follow same probability distribution, which may suggest k-means clustering to be combined with a probabilistic classifier. K-means clustering [2] and naive Bayes classifier algorithms are developed [3] and applied on APS operation data of lifetime and top-up efficiency. As shown in Fig. 1, the clustering agree with the true label for two operation mode with different bunch fill pattern and lattice chromaticity.

Considering the operation data for one operation mode, it would be interesting to analyze and possibly understand the variations on beam lifetime and top-up efficiency. As shown in Fig. 2, the optimum number of classes is automatically determined to be 4 by the elbow method. The clustering in Fig. 2 reasonably agree with the Gaussian kernel density estimation as shown in Fig. 3. It is observed that when lifetime is low the top-up efficiency variance is small, and vice versa. With some investigations on other archived data, it seems that the storage ring chromaticity was increased for the lower lifetime cluster, most likely to stabilize some collective instabilities. Blue cluster may be the preferred

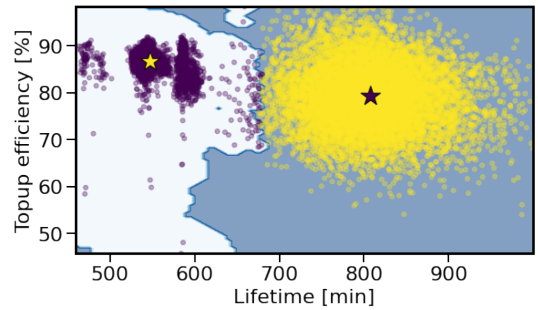

Figure 1: Lifetime and top-up efficiency of two APS operation mode, grouped with unsupervised k-means clustering followed by naive Bayes classifier, given that k = 2.

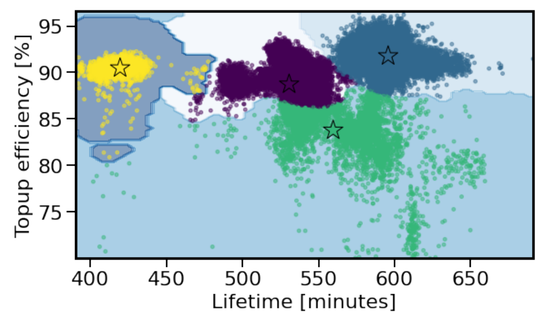

Figure 2: Lifetime and top-up efficiency of one fill pattern, by k-means clustering plus naive Bayes classifier where k = 4.

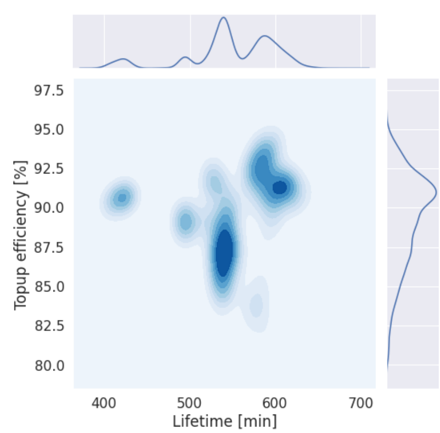

Figure 3: Beam lifetime and top-up efficiency of one fill pattern, kernel density estimation with several clusters.

area for optimized operations, where both beam lifetime and top-up efficiency are good. It seems that this cluster is from the weeks following machine start-up.

DEEP LEARNING ON MODELING AND PREDICTION OF BEAM LIFETIME

Recently deep learning by artificial neural networks has successful applications in many fields, such as image and

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† yisun@anl.gov

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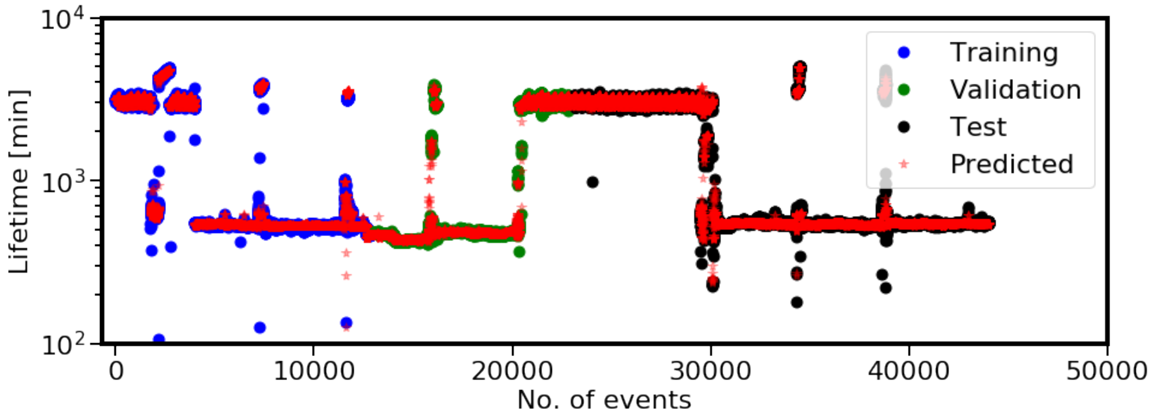

Figure 4: True APS beam lifetime of the training, validation and test datasets, as compared to the predictions from artificial neural network. Reasonable agreement is achieved.

voice recognitions, natural language processing and translation, online and offline advertising, and automatic driving. An in-house artificial neural network code has been developed, benchmarked [4], and employed for this study.

APS operation history data is collected on beam lifetime, and the following observable parameters which are expected to have impact on beam lifetime.

- Total energy loss from insertion devices
- Total stored beam current
- Transverse emittance ratio
- RF gap voltage
- Linear chromaticity in both transverse planes
- Number of RF buckets filled in the storage ring
- Vacuum pressure at limiting apertures.

The collected APS operation dataset is divided into training, validation and test datasets. Several different stored bunch pattern are covered by this dataset, including 24 bunches, 324 bunches, hybrid bunch fill pattern and others. As shown in Figs. 4 and 5, it seems to be possible to accurately predict the APS beam lifetime, with an RMS error of 2 – 3% of true beam lifetime. It may be possible to estimate the level of impacts from the previously discussed several observable parameters. Shown in Fig. 6 is the sum on the absolute value of weights in the first hidden layer of the trained artificial neural network, which may provide some insights on the importance of each feature. For example, this analysis seems to agree with the fact that APS beam lifetime is highly correlated with bunch fill pattern, and transverse emittance ratio.

DEEP LEARNING AND PREDICTION ON TOP-UP EFFICIENCY

A similar study is performed on the APS top-up injection efficiency, top-up beam current and all the beam loss monitors. Two different APS stored bunch pattern of 24 bunches

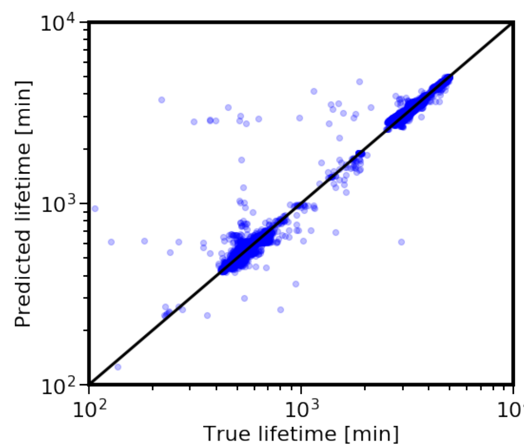

Figure 5: True APS beam lifetime compared with the artificial neural network predictions, for the test dataset.

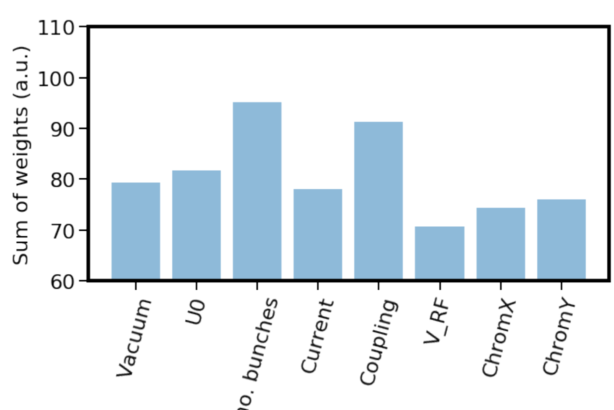

Figure 6: Estimation on impacts from different observable parameters on APS stored beam lifetime.

and hybrid bunch mode are included in the collected dataset, which is divided into training, validation and test datasets. As shown in Fig. 7, it is observed that the lower top-up efficiency section is for hybrid bunch fill pattern.

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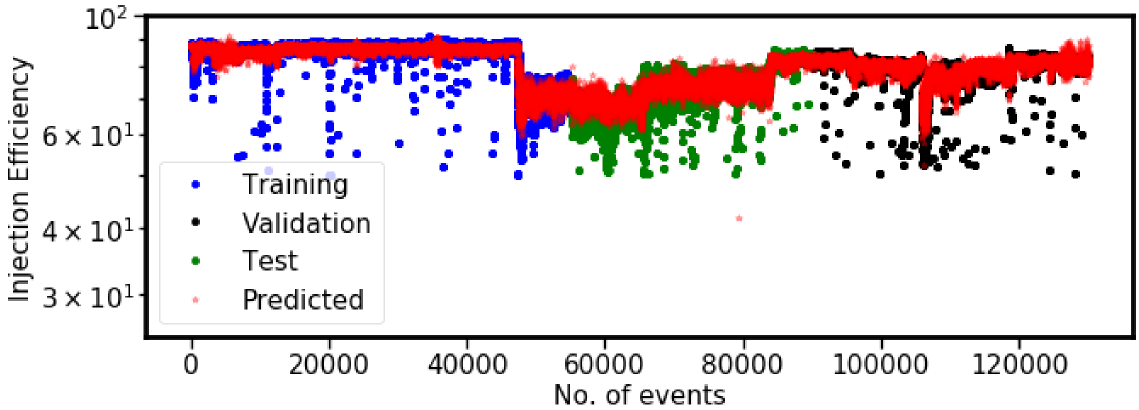

Figure 7: True APS top-up efficiency of the training, validation and test datasets, which are compared to the predictions from artificial neural network, where reasonable agreement is achieved.

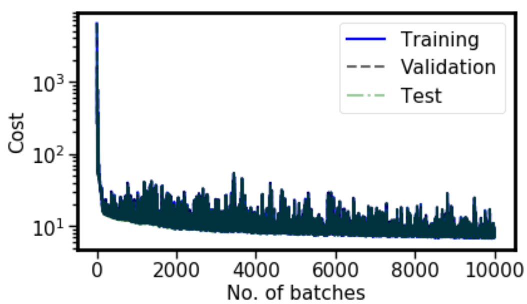

Figure 8: Overall cost alongside the artificial neural network training progress, for the training, validation and test datasets.

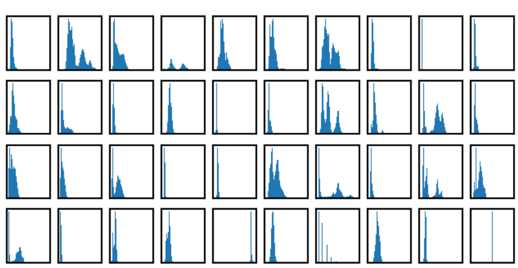

Figure 9: Histograms on all the beam loss monitors data, where it is observed that some beam loss monitors' reading may not be calibrated or precise.

With the trained artificial neural network (training progress in Fig. 8), it seems possible to accurately predict the APS top-up injection efficiency from top-up beam current and all beam loss monitors. The prediction may work in regardless of the stored bunch pattern of 24 bunches and hybrid bunches mode. As illustrated by the histograms of all the beam loss monitors in Fig. 9, the readings of some beam loss monitors may not be calibrated or precise. On the other hand, this may demonstrate the capability of artificial neural network in working on arbitrary and noisy data. A bimodal distribution is observed on histograms of most beam loss monitors, which agrees with the fact that there are two bunch fill patterns in the dataset.

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