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ANOMALY DETECTION BY PRINCIPAL COMPONENT ANALYSIS AND AUTOENCODER APPROACH*

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Abstract

Several different approach are employed to identify the abnormal events in some Advanced Photon Source (APS) operation archived dataset, where dimensionality reduction are performed by either principal component analysis or autoencoder artificial neural network. It is observed that the APS stored beam dump event, which is triggered by magnet power supply fault, may be predicted by analyzing the magnets capacitor temperatures dataset. There is reasonable agreement among two principal component analysis based approaches and the autoencoder artificial neural network approach, on predicting future overall system fault which may result in a stored beam dump in the APS storage ring.

OVERVIEW

Anomaly detection is the operations to identify the abnormal events or the outliers from some unlabeled dataset, which is widely employed in the predictive condition monitoring of complex operating systems. Examples of anomaly detection include bank fraud detections system, spam emails filtering, and operating machine fault monitoring system. For the health monitoring of such complex systems, usually there are huge number of different sensors installed, which are employed to monitor the operating conditions of different sub-systems. To collectively analyze the data which are collected by these sensors, it may be preferred to perform dimensionality reduction on the raw sensors data, as most likely only the most critical extracted features may be relevant. There are two popular approach of dimensionality reduction, principal component analysis (PCA) and autoencoder artificial neural network, which will be employed and discussed in the following sections of the paper.

The Advanced Photon Source storage ring light source is a third generation light source starting operation in the 1990s [1]. Occasionally there is stored beam dump resulted from APS technical systems failures, which introduces operation interruptions for the photon users. Among these technical systems, the power supply data of all the magnets are proposed to be analyzed [2]. The magnet current and temperatures data are collected on all the major magnets in the APS storage ring, including steering dipole correctors, quadrupole magnets, and sextupole magnets. Some samples on normalized data of these magnets are shown in Fig. 1, where there is an event for magnet power supply fault and APS stored beam dump.

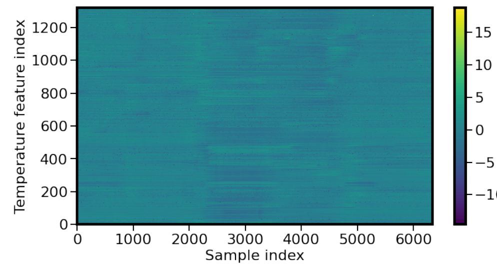

Figure 1: Magnets temperature data from APS operation archive, the beam dump occurring near samples index of 3000.

PRINCIPAL COMPONENT ANALYSIS

Principal component analysis (PCA) technique is usually employed to linearly transform a high dimensional data into a low dimensional one, where most of the variance in the original dataset is preserved by the principal components. Hence it is expected that the most critical features in the original dataset would be preserved in the PCA transformed new dataset. By employing two principal components, and applying principal component analysis fit and transformation [3] operations on the APS magnets capacitor temperatures dataset, a new dataset is generated and analyzed by Gaussian kernel density estimation, as shown in Fig. 2. It is observed that there are one main nominal cluster and several outlier clusters. For the next steps of analysis, five principle

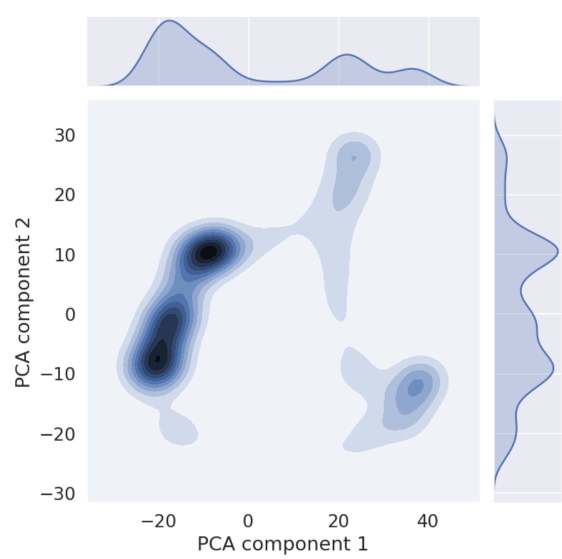

Figure 2: Gaussian kernel density estimation of the two principal components from the PCA transformation, showing the main nominal cluster and several outlier clusters.

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components are preserved in the PCA process. The five by five covariance matrix [4] of the PCA tranformed training dataset is shown in Fig. 3.

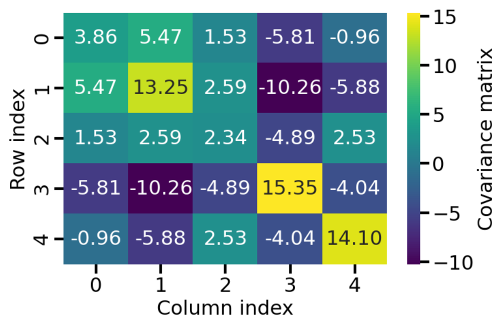

Figure 3: Five by five covariance matrix of the PCA tranformed training dataset, showing correlations among the five preserved principal components by the PCA process.

KERNEL DENSITY ESTIMATION

Kernel density estimation is one way to post-process the principal components dataset. The idea is that the dataset for normal operations of the complex system would follow some arbitrary distribution, and it may be possible to describe this distribution by employing kernel density estimation. The samples in the test dataset are then evaluated on the acquired probability density function. In case that lower probability is observed for extended time, it may indicates that some systems fault is approaching. Kernel density estimation [5] are performed on the five principle components of magnet capacitor temperatures data. As shown in Fig. 4, the probability density distribution of the probability density in training dataset follows some arbitrary distribution, which is calculated by the kernel density estimation. The APS stored beam current is plotted alongside the probability density estimation of training and test datasets, as shown in Fig. 5. When the probability density is decreasing below the alarm threshold, which is determined by the training dataset, the

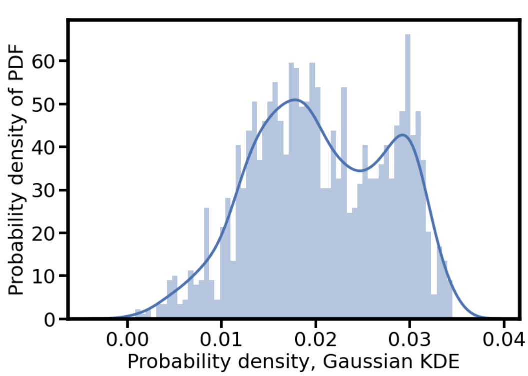

Figure 4: Probability density distribution of the probability density as evaluated by the Gaussian kernel density estimation on the principal components.

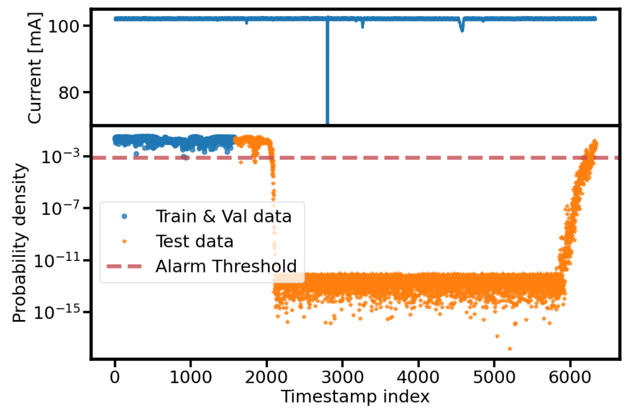

Figure 5: Top: APS stored beam current dropping to zero at the point of magnet trip and stored beam dump. Bottom: the probability density from the Gaussian kernel density estimation, for training, validation and test datasets. Red dashed line denotes the alarm threshold determined by the training dataset.

APS storage ring is approaching a fault event of stored beam dump.

MAHALANOBIS DISTANCE

The mahalanobis distance $\mathbf{MD}(\mathbf{x_i}, \mathbf{x_0})$ from one sample $\mathbf{x_i}$ to the centroid $\mathbf{x_0}$ of all the samples is defined as a generalization of the Euclidean distance, which can be calculated using the inverse of the covariance matrix M_{cov} of the principal components $\mathbf{x}$.

$$\mathbf{MD}(\mathbf{x_i}, \mathbf{x_0}) = \sqrt{(\mathbf{x_i} - \mathbf{x_0})^{\mathbf{T}} \cdot \mathbf{M_{cov}^{-1}} \cdot (\mathbf{x_i} - \mathbf{x_0})} \quad (1)$$

where $\mathbf{M_{cov}^{-1}}$ denotes the inverse matrix of the covariance matrix.

Shown in Fig. 6 is the probability density distribution of the mahalanobis distance to the centroid in the principal components basis space, which is calculated for the test dataset.

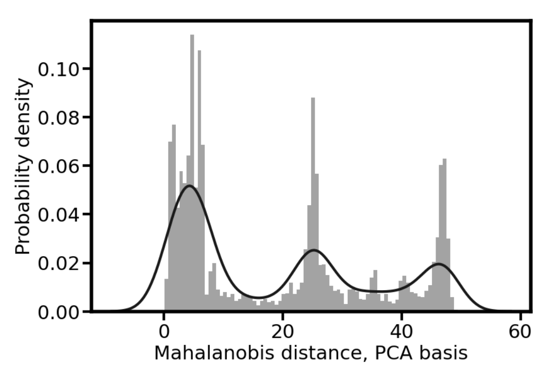

Figure 6: Probability density distribution of the mahalanobis distance to the centroid in the principal components basis space, for the test dataset.

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The calculated mahalanobis distance for all the datasets in the principal components basis is shown in Fig. 7 alongside the APS stored beam current, where the alarm threshold is determined by the mahalanobis distance of the training dataset. It is observed that the mahalanobis distance goes above the alarm threshold when the APS storage ring is approaching an anomaly condition, which is a stored beam dump from magnet fault. The mahalanobis distance reaches its maximum around the stored beam dump event, and slowly recovers to normal value afterwards.

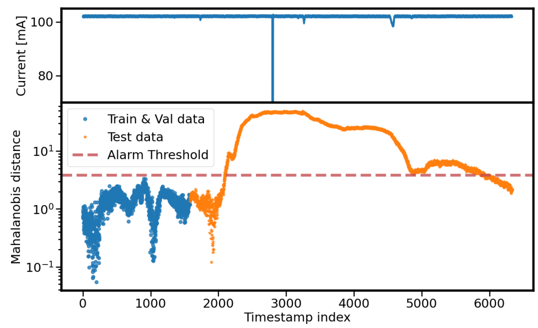

Figure 7: Top: APS stored beam current drops to zero at the point of magnet trip and beam dump. Bottom: the mahalanobis distance to the centroid in the principal components space, for training/validation and test datasets. Red dashed line denotes the alarm threshold determined by training dataset.

AUTOENCODER

Autoencoder neural network is a special category in the family of artificial neural networks, which is usually employed as an unsupervised learning approach for dimension reduction and exceptions detection. As shown by an architecture sketch in Fig. 8, autoencoder neural network is composed of an encoder part and a decoder part, which are arranged in a symmetric way. Compared with PCA, autoencoder neural network may perform nonlinear transformations in addition to the linear transformations. The autoencoder neural network is trained on the training and validation datasets which are same as used in the PCA process. The reconstruction loss of mean squared errors is calculated on the training, validation and test datasets.

Comparing Fig. 9 with Figs. 5 and 7, it is observed that the reconstruction loss of autoencoder neural network follows a similar path as the probability density and the mahalanobis distance from the previous two PCA approaches. It seems that all these three approaches may identify abnormal conditions and possibly predict a future fault of the overall system. By analysis on other datasets, it is also observed that the reconstruction loss may show different pattern, when the stored beam dump is introduced by power supply fault of different magnet type.

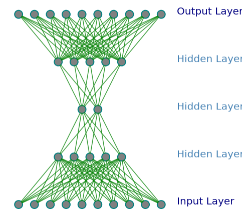

Figure 8: An example for autoencoder neural network architecture. The middle hidden layer represents the latent space with two latent variables.

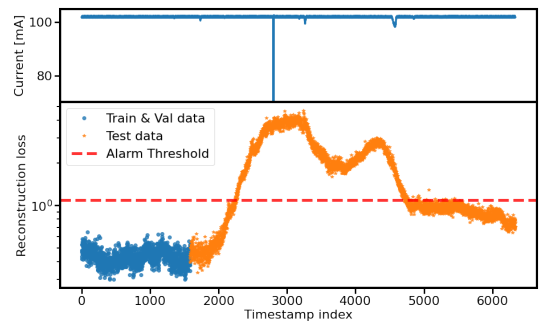

Figure 9: Top: stored beam current dropping to zero at the point of magnet trip and stored beam dump. Bottom: the reconstruction loss as mean squared errors of autoencoder neural network, for training, validation and test datasets. Red dashed line denotes the alarm threshold.

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