Performance evaluation of Anomaly Detection in Energy Consumption between Statistical Method and Undercomplete Autoencoder

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***Abstract*—This paper is concerned about the use of unsupervised learning algorithms in power consumption data, as well as the comparison of the performance between statistical method and Undercomplete Autoencoder in classification. As power consumption varies over time, therefore the labeled data created by that, becomes obsolete over times. Therefore, supervised learning is not a viable method in the prediction of energy consumption.**

I. Introduction

In modern days, the amount of energy consumption is becoming a more serious issue as several companies and industries are addressing this issue in order to contain their expenses as unexpected variations can incur additional operational costs to their facilities. These fluctuations in electricity consumption can arise from various factors such as excessive use of heavy equipment like electric heaters in winters, room coolers during the summers etc. In order to detect such variations or anomalies, anomaly detector algorithm is designed and implemented on the provided data. Presently, it is very difficult to predict the energy consumption anomalies precisely, since there are many factors influencing the energy usage, such as weather condition, building structure and characters, geographic location, occupancy [1] and operation of appliances [2], [3].

II. Related Works

Previous studies in data-driven building energy consumption prediction have utilized several methods such as Engineering methods [4], statistical method [5], Artificial Neural Networks (ANN) [6], [7], support vector machines (SVM) [8], fuzzy logic and grey model techniques [9], decision trees [10] etc.

Also there have been some studies which compared the effectiveness of different algorithms in energy consumption prediction by comparing the results of two or more algorithms on a similar dataset. For example, Li et al. [8] compared SVM and Back Propagation Neural Network (BPNN); Borges et al. [11] compared SVM and Autoregressive (AR) Model; Xuemei et al. [12] compared LS-SVM and BPNN; Liu and Chen [13] compared Support Vector Regression (SVR) and ANN; Penya et al. [14] compared AR Model, ANN,autoregressive integrated moving average(ARIMA), and Bayesian Network; Platon et al. [15] compared ANN and Case based Reasoning (CBR); Jain et al. [16] compared SVM and MLR; (this paper linked from somewhere else) Hou et al. [17] compared ARIMA and ANN (need to download paper); Fan et al. [18] compared MLR, ARIMA, SVM, RF, MLP, BT, MARS, and kNN; Chou and Bui [19] compared ANN, SVM, CART, CHAID, and GLR; Edwards et al. [20] compared MLR, FFNN, SVM, LS-SVM, HME-FFNN, and FCM-FFNN; Li et al. [21], [22] compared SVM, BPNN, Radial Basis Function Neural Network(RBFNN), and General Regression Neural Network (GRNN); Dagnely et al. [23] [22] compared Ordinary Least Squared (OLS) Regression and SVR; Massana et al. [24] compared MLR, MLP, and SVR; and Fernandez et al. [25] compared AR, polynomial model, ANN, and SVM.

III. Methodology

A. Statistical Method

In order to detect outliers in the provided data, Tuckey's test was performed on the elements of feature vector, which involves the calculation of median of training data which is referred to $Q2$ and then again median of values lesser and greater than that of $Q2$ is calculated. Median of values lower than $Q2$ is refereed as $Q1$ (lower quartile) and those having greater than $Q2$ is referred as $Q3$ (upper quartile) as shown in Figure 8.

After determining $Q1$ and $Q3$, then Interquartile Range (IQR) is calculated by subtracting the value at $Q3$ by $Q1$.

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$$IQR = Q3 - Q1 \tag{1}$$

After calculating the IQR, we use it to calculate the Tuckey's Fences or Inner Fences by the following equation,

$$InnerFenceLowerLimit = Q1 - \alpha(IQR) \tag{2}$$

$$InnerFenceUpperLimit = Q1 + \alpha(IQR) \tag{3}$$

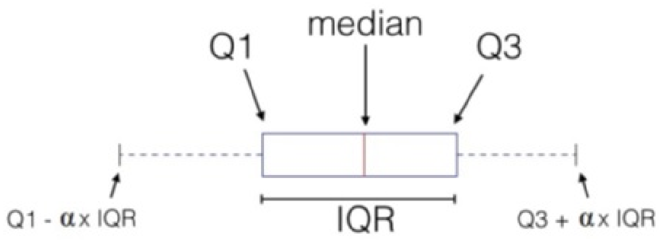


Fig. 1: Depiction of quartiles as used in the detection and removal of Outliers.

where,
α is the factor which varies the inner fence limits.

Any value lying beyond inner fence limits (upper and lower) can be considered as an outlier, and therefore, it is removed. A sample result of designed outlier detection algorithm is shown in Figure 3.

B. Autoencoders

An autoencoder always consists of two parts, the encoder and the decoder, which can be defined as transitions ϕ and ψ such that:

$$\phi : \mathcal{X} \rightarrow \mathcal{F} \tag{4}$$

$$\psi : \mathcal{F} \rightarrow \mathcal{X} \tag{5}$$

$$\phi, \psi = \underset{\phi,\psi}{\arg\min} \ \|X - (\phi \circ \psi)X\|^2 \tag{6}$$

In a simple case, if there is one hidden layer, the encoder stage of an autoencoder takes the input $\mathbf{x} \in \mathbb{R}^d = \mathcal{X}$ and maps it to $\mathbf{z} \in \mathbb{R}^p = \mathcal{F}$.

$$\boldsymbol{z} = \boldsymbol{\sigma}(\boldsymbol{W}\boldsymbol{x} + \boldsymbol{b}) \tag{7}$$

This image $\mathbf{z}$ is usually referred to as *code*, *latent variables* or *latent representation*. Here, σ is an element-wise activation function such as sigmoid function, hyperbolic tangent or a rectified linear unit. W is weight matrix and b is a bias vector. After that, the decoder stage of the autoencoder maps $\mathbf{z}$ to the reconstruction $\mathbf{x'}$ of the same shape as $\mathbf{x}$.

$$\boldsymbol{x'} = \boldsymbol{\sigma'}(\boldsymbol{W'}\boldsymbol{z} + \boldsymbol{b'}) \tag{8}$$

where, $\boldsymbol{\sigma'}$, $\boldsymbol{W'}$ and $\boldsymbol{b'}$ for the decoder may differ in general from the corresponding $\boldsymbol{\sigma}$, $\boldsymbol{W}$ and $\boldsymbol{b}$ for the encoder, depending on the design of the autoencoder.

Autoencoders are also trained to minimise reconstruction errors (such as squared errors):

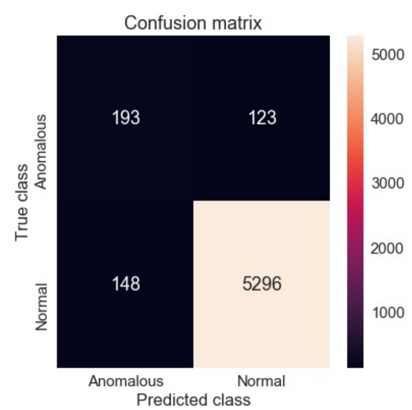
$$\boldsymbol{\mathcal{L}}(\boldsymbol{x}, \boldsymbol{x'}) = \|\boldsymbol{x} - \boldsymbol{\sigma'}(\boldsymbol{W'}(\boldsymbol{\sigma}(\boldsymbol{W}\boldsymbol{x} + \boldsymbol{b})) + \boldsymbol{b'})\|^{\mathbf{2}} \tag{9}$$

where, $\boldsymbol{x}$ is usually averaged over some input training set.

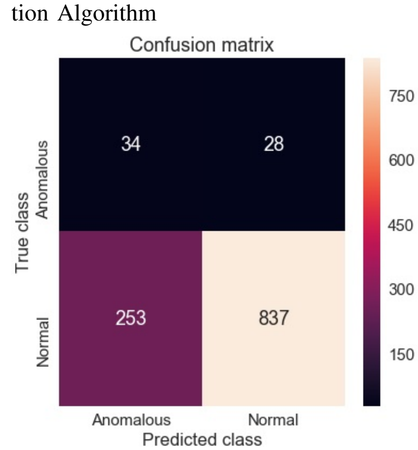
If the feature space $\boldsymbol{\mathcal{F}}$ has lower dimensionality than the input space $\boldsymbol{\mathcal{X}}$, then the feature vector $\boldsymbol{\phi}(\boldsymbol{x})$ can be regarded as a compressed representation of the input $\boldsymbol{x}$. If the hidden layers are larger than the input layer, an autoencoder can potentially learn the identity function and become useless. However, experimental results have shown that autoencoders might still learn useful features in these cases. In case of Undercomplete autoencoders, $\boldsymbol{\mathcal{F}}$ has lower dimensionality than the input space $\boldsymbol{\mathcal{X}}$, then the feature vector $\boldsymbol{\phi}(\boldsymbol{x})$ can be regarded as a compressed representation of the input $\boldsymbol{x}$

C. Performance Comparison between Anomaly Detection and Autoencoder

In Fig 2, we are comparing the accuracy of prediction of both algorithms with manually classified energy data of two stores using confusion matrices.



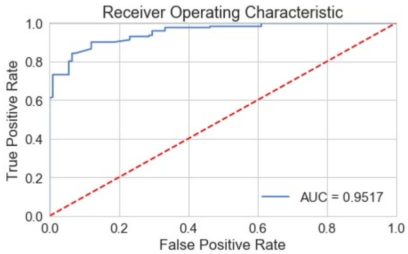
(a) Confusion Matrix of Anomaly Detection Algorithm



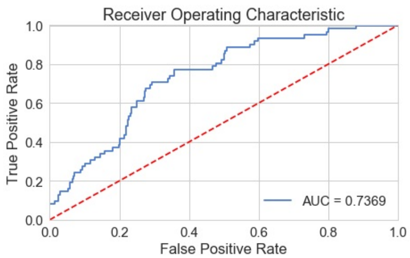
(b) Confusion Matrix of Autoencoder.

Fig. 2: Confusion Matrices

The same dataset which was used to make confusion matrices in Fig 2 is used to plot Receiver Operating Characteristics curves in Fig 3.



(a) ROC curve of Anomaly Detection Algorithm.



(b) ROC curve of Autoencoder.

Fig. 3: ROC curves

As we can see from the comparison of Fig 2 and Fig 3, we can interpret that the performance of Statistical method which is based on Tuckey's test performed remarkably better with around 95% similarity with manual classification. Whereas, classification using Autoencoder performed adequately with around 70-75% correlation with manually classified data.

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