Clustering Quality of a High-dimensional Service Monitoring Time-series Dataset

Farzana Anowar[1,2,a], Samira Sadaoui[1,b] and Hardik Dalal[2]

[1] *University of Regina, Regina, Canada*

[2] *Ericsson Canada Inc., Montreal, Canada*

Keywords: High-dimensional Time-series Dataset, Clustering Quality, Data Clustering, Data Imputation, Deep Learning.

Abstract: Our study evaluates the quality of a high-dimensional time-series dataset gathered from service observability and monitoring application. We construct the target dataset by extracting heterogeneous sub-datasets from many servers, tackling data incompleteness in each sub-dataset using several imputation techniques, and fusing all the optimally imputed sub-datasets. Based on robust data clustering approaches and metrics, we thoroughly assess the quality of the initial dataset and the reconstructed datasets produced with Deep and Convolutional AutoEncoders. The experiments reveal that the Deep AutoEncoder dataset's performances outperform the initial dataset's performances.

1 INTRODUCTION

In industry, an incredible amount of data is produced on a daily basis (Anowar and Sadaoui, 2021a; Anowar and Sadaoui, 2020). Sometimes, data are not appropriately captured, which may be caused by human errors, or sensor malfunction, resulting in data incompleteness (i.e., missing values). Additionally, in the presence of high dimensionality in the data, the training process becomes complicated for Machine Learning Algorithms (MLAs), leading to the model overfitting and lowering the predictive performance (Jindal and Kumar, 2017), (Anowar and Sadaoui, 2021b). These two issues become more critical for time-series datasets since the latter are collected over large time frames. As a consequence, there are much more chances of having missing values and high dimensionality, which necessitate special attention from the experts when dealing with these data (Rani and Sikka, 2012).

Based on an industrial application, we construct a new End-to-End (E2E) service monitoring time-series dataset so that users (developers, DevOps engineers, IT managers, and site reliability engineers) can respond to system-wide performance changes, monitor the services' availability, and optimize the resource utilization. For this purpose, we first collect data from multiple sub-servers over six weeks. However, the collected sub-datasets are heterogeneous in terms of feature spaces and sizes. Before merging the sub-datasets, we address the issue of data incompleteness for each sub-dataset separately. We tackle missing values with several imputation techniques carefully and keep the optimally imputed sub-datasets only. Subsequently, we fuse the imputed sub-datasets based on the time-stamp feature to produce the final time-series service monitoring dataset. The latter is unlabelled, temporal, and high dimensional. Since the dataset is new and complex, we need to evaluate its quality before using it for any decision-making task. This study compares several clustering techniques on this very high-dimensional dataset and its reconstructed equivalent datasets. To this end, first, we handle the high dimensionality issue and second adopt data clustering methods, including two conventional and two recent time series-based algorithms, in which the dataset is divided into several optimal groups. Since high dimensional data brings computational challenges for developers, we use Deep and Convolutional Autoencoders to improve our dataset's quality and then assess the quality of the reconstructed datasets using the same clustering methods.

Many efficient dimensionality reduction methods reduce the feature space effectively; however, they are unable to recover the original data (Anowar et al., 2021). In contrast, the AutoEncoders are effective

[a] https://orcid.org/0000-0002-1535-7323

[b] https://orcid.org/0000-0002-9887-1570

Anowar, F., Sadaoui, S. and Dalal, H.
Clustering Quality of a High-dimensional Service Monitoring Time-series Dataset.
DOI: 10.5220/0010801400003116
In *Proceedings of the 14th International Conference on Agents and Artificial Intelligence (ICAART 2022) - Volume 2*, pages 183-192
ISBN: 978-989-758-547-0; ISSN: 2184-433X

not only in lowering the dimensionality but also in reconstructing the original data. We also make sure not to lose much information while reconstructing the data. Lastly, we thoroughly compare the quality of the initial and reconstructed datasets based on the optimal clusters using several quality metrics to show the efficacy of the reconstructed datasets. The obtained best clusters will be used for any further decision-making tasks in the ML domain. We utilize AutoEncoders to showcase that the reconstructed feature space yields better clustering than the original dataset. Our experimental results demonstrate that the clustering performances of the reconstructed dataset with Deep AutoEncoder (DAE) increased significantly over the clustering performances with the initial dataset. To the best of our knowledge, no prior research provided a thorough analysis of the clustering quality of a high-dimensional time-series dataset that comes with missing values.

We structure the paper as follows. Section 2 discusses recent data clustering methods for assessing the quality of high dimensional datasets. Section 3 presents the preprocessing and the fusion process to build the target datasets. Section 4 describes the clustering approaches and their quality evaluation metrics. Section 5 develops two deep learning methods to reconstruct the dataset. Section 6 and Section 7 perform several experiments to assess the clustering quality of the initial and reconstructed datasets. Section 8 compares all the clustering quality results. Section 9 concludes our work with future work.

2 RELATED WORK

We examine notable studies that utilized diverse data clustering methods to deal with high-dimensional datasets specifically and reduce their complexity. For instance, the authors in (Dash et al., 2010) combined the dimensionality reduction method named Principal Component Analysis (PCA) and the data clustering technique K-means. First, to make K-means more effective, they proposed to utilize the instances that have the maximum squared Euclidian distance (among all the instances) as the initial centroids for the clustering task. Next, they compared the performances of the original K-means and the new proposed approach using the reduced PCA dataset. They showed that the results produced with the proposed centroid selection method are more accurate, easy to visualize, and the time complexity was substantially decreased.

Any feature selection technique for high dimensional datasets is assessed from two perspectives (Song et al., 2011): efficiency and effectiveness, where efficiency is related to the time required to obtain the optimal sub-group of features, and effectiveness concerns the quality of this sub-group. A fast clustering-based feature selection approach is proposed in (Song et al., 2011), which operates in two phases. Firstly, all the features are partitioned into clusters based on the ”graph-theoretic clustering” technique to select the subsets of features, and secondly, from each cluster, the most relevant feature that is closely connected to the target variable is chosen again to provide the best selection of features. The authors adopted the clustering method called ”Minimum-Spanning Tree” to prove the competence of the proposed method and carried out experiments to evaluate the performances between the proposed method and several existing feature selection algorithms. The experiments demonstrated that the proposed approach returned reduced subsets of features and improved the performances of the classification task.

For tackling the data dimensionality, Feature Selection Algorithms (FSAs) were mainly adopted in the literature. However, FSAs fail for large-scale feature spaces. Hence, the authors in (Chormunge and Jena, 2018) addressed this problem by integrating a clustering technique with a correlation measure to generate a good subset of features. They first eliminated the insignificant features using K-means clustering, and later, the non-redundant features are chosen by utilizing the correlation metric from each cluster. For the experimental purpose, they used microarray and text datasets to evaluate the proposed method and compared the performances with two other FSAs, ReliefF and Information Gain, using the Naïve Bayes classifier. The experimental results showed that the most representative features were chosen by varying the number of relevant features and provided better accuracy than the other two FSAs.

Detecting outliers is an essential ML task because outliers may carry important information. However, in the case of high-dimensional datasets, outliers may lead to worse performances. Therefore, the authors in (Messaoud et al., 2019) developed a hybrid framework named ‘Infinite Feature Selection DBSCAN’ (InFS-DBSCAN) to decrease the dimensionality of datasets and identify outliers efficiently using clustering techniques. They first removed insignificant features by selecting the k-most relevant features from the high dimensional data space and then adopted the DBSCAN algorithm to detect outliers. Two real-world datasets were used for the experiments to compare the performances of the proposed approach with DBSCAN and FS-DBSCAN clustering in terms of the clustering accuracy and error rate. For both datasets, the proposed approach outperformed the other methods.

3 TIME-SERIES DATASET CONSTRUCTION

The data we use for the experiments was collected through Prometheus from October 26 to December 03, 2020, every 15 seconds for many available services. The data is extracted from a monitoring service that comes with three critical characteristics:

1. By nature data is high dimensional and temporal (time series).
2. Data was collected from different sub-servers, so it is stored and processed separately.
3. Data has many missing values due to the nature of the applications hosted on the servers and network/hardware/software failures.

More precisely, we retrieve data from 48 sub-servers (in CSV format). The extracted sub-datasets possess different sizes and sets of features. After examining all the data, we found two types: Counter and Gauge. The Counter type indicates a single monotonically growing counter whose value can either increase or be reset to zero on restart (Prometheus, 2021). The Gauge type denotes a single numerical value that can arbitrarily go up and down (Prometheus, 2021).

3.1 Handling Missing Values in Each Sub-server Data

Nevertheless, all the sub-server files contain missing values. There are several options to tackle those values, such as imputation, removal of data with missing values (good option only when missing values are rare), replacement with constant values (i.e. 0 or 1). The last two options are not practical if many missing values are present, like in some of our sub-servers files. Hence, we choose three imputation techniques: (1) KNN Imputation, (2) MissForest Imputation, and (3) SimpleImputer using the mean value. KNN imputation is easy to implement and fast, MissForest can handle mixed data type (numerical and categorical) and works efficiently with high-dimensional data, and SimpleImputer performs much faster and can also tackle mixed data. (Jadhav et al., 2019), (Pedregosa et al., 2011), (Stekhoven and Bühlmann, 2012).

We apply the three techniques to each sub-server dataset separately to obtain relevant imputed values.

Table 1: Silhouette-Index Scores for Data Imputation.

Sub-server	SimpleImputer	KNN	MissForest
#1	**0.996663641**	0.996662706	0.995631504
#3	0.932876262	**0.932890974**	0.932648194
#4	0.493330594	0.523756138	**0.549322423**

Furthermore, we utilize the “Silhouette Index” to assess the new values. The imputation method that returns the best (higher) Silhouette score is selected for each file. Table 1 reports the Silhouette scores for three sub-servers, as examples. For different sub-server files, different methods are needed to achieve the best data quality. Indeed, we obtain 31 optimally imputed sub-datasets with SimpleImputer, 4 optimally imputed data with KNN imputation, and 13 optimally imputed data with MissForest. We may note that MisssForest necessitated more computational time than the two others.

3.2 Fusing Heterogeneous Sub-server Datasets

As mentioned earlier, we obtain 48 optimally imputed sub-datasets. Subsequently, we conduct the “Inner Join” procedure to merge the many heterogeneous sub-datasets by considering the time-stamp column as the key component. This procedure keeps the instances from the participating files as long as there is a match between the key columns. It returns all the rows where the key component (here time-stamp) of one file is equal to the key records of another file. As a result, we produce the final E2E service monitoring dataset consisting of 3,100 features and 53,953 instances over 6 weeks (39 days). This dataset is of a large scale and highly dimensional.

We use a simple example to explain the Inner Join procedure (Figure 1) where we have two separate databases: Product and Customer. After applying Inner Join to both files using the ProductID as the key column, we obtain only 1 row (with 10 features) as the two files have only one common value (101). Also, notice that the attribute City is present in both databases, and Inner Join produces 2 different attributes (City_x and City_y) for the final output, as the first one denotes the product’s warehouse location and the second one is the delivery location.

Figures 2 and 3 plot two features named ‘Requests1’ and ‘Responses1’ (selected randomly) from the E2E service monitoring dataset. In Figure 2, data has either went up or is set to 0, which implies that the feature ‘Request1’ contains Counter-type data. In Figure 3, data has gone up and down arbitrarily, which shows that the feature ‘Responses1’ is of the Gauge type.

	ProductID	ProductName	Category	Price	City
0	101	Watch	Fashion	199.0	Washington
1	102	Bag	Fashion	2350.5	Regina
2	103	Shoes	Fashion	1999.0	Paris
3	104	Smartphone	Electronics	25999.0	Berlin
4	105	Pen	Study	32.0	Toronto

(a) Product DB.

	ID	Name	Age	ProductID	PurchasedProduct	City
0	1	Oliver	22	101	Watch	Vancouver
1	2	Dave	20	0	NA	Montreal
2	3	Corrie	32	107	Oil	Dhaka
3	4	Isabella	17	0	NA	New York
4	5	David	34	109	Shoes	Berlin

(b) Customer DB.

	ProductID	ProductName	Category	Price	City_x	ID	Name	Age	PurchasedProduct	City_y
0	101	Watch	Fashion	199.0	Washington	1	Oliver	22	Watch	Vancouver

(c) Inner Join of Product and Customer.

Figure 1: Concept of Inner Join.

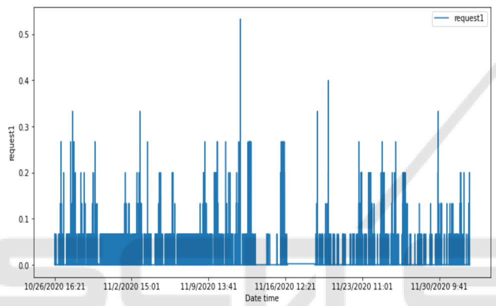


Figure 2: Feature ‘Request1’ (Counter Type).

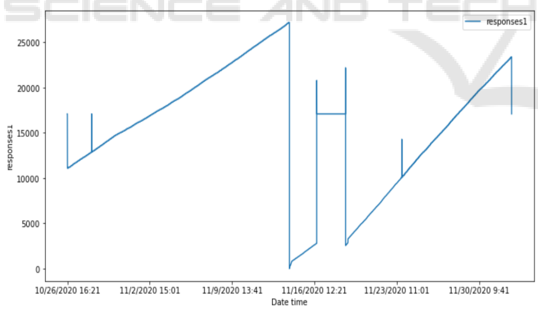


Figure 3: Feature ‘Responses1’ (Gauge Type).

3.3 Normalizing the New Feature Space

After examining the final dataset, we observe that most features (80.64%) have quite small values, and 19.36% of features have very high values. The big value disparities between features require to re-scale the entire dataset. Using the min-max scaler in Python, we try multiple ranges, including [0-1], [0-10], [0-50], [0-100] for the AutuEncoders’ loss optimization, and obtain [0-1] is the best range to re-scale the dataset for the experiment.

4 CLUSTERING APPROACHES AND METRICS

We assess the quality of the new dataset through unsupervised learning using data clustering since it is unlabeled. It is critical for any unsupervised ML task to obtain high-quality clusters in order to find the hidden patterns or unknown correlations in a dataset (Wu et al., 2020). To this end, we select different clustering techniques: partition-based, time-series-based, and density-based, described below:

- K-means is a widely employed clustering technique in the literature (Niennattrakul and Ratanamahatana, 2007), (Aghabozorgi et al., 2015).
- TS-Kmean and TS-Kshape are both designed explicitly for time series with a high dimensionality (Tavenard et al., 2020). The specialty about TS-Kmean is that it can weigh the time-stamps automatically based on the time-span’s significance during the clustering operation (Huang et al., 2016). TS-Kshape computes the distance measure and centroids using the normalized cross-correlation of two time series for each iteration, and update the assignments of the clusters (Paparrizos and Gravano, 2015). Both methods have only one hyper-parameter (max_iter).
- HDBSCAN has one hyper-parameter (min_cluster_size) compared to other density-based methods. It can handle highly dense data, like ours. Besides, it can tackle the varying density issue, which the standard DBSCAN method cannot (Saul, 2017). Additionally, HDBSCAN does not require knowing the count of clusters beforehand, unlike the three previous methods (McInnes and Healy, 2017).

A well-known fact about K-means is that it takes more time to converge for large-scale datasets (Prabhu and Anbazhagan, 2011), like ours. To fix this issue, we utilize K-means++ as the initializer inside the K-means algorithm to make the convergence much faster. For utilizing TS-Kmean and TS-Kshape, we first import ‘tslearn’, a Python machine learning package for time-series datasets. Also, for TS-Kmean, we set max_iter to 50 and include the initializer K-means++ as well, and for the cluster assignments, we use the Euclidean distance. Moreover, for TS-Kshape, we set max_iter to 100. For the three first methods, we search for the optimal number of clusters using Elbow, Silhouette Coefficient, and Calinski-Harabasz (CH) Index. Lastly, we allocate min_cluster_size to 2000 for HDBSCAN, as we believe out of 53,953 data, the minimum 2000 data ($\approx$

26%) for a cluster is good enough.

To assess the quality of the produced clusters by the four methods, we utilize the following quality metrics, described below:

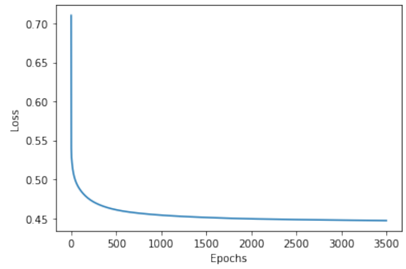
- Sum of Squared Error (SSE) that identifies how internally coherent each cluster is. The lower the SSE, the better the cluster is (Pedregosa et al., 2011).
- Davies-Bouldin (DB) Index that defines the average similarity of each cluster, i.e., the intra-cluster distance should be minimum. Hence the lower, the better (Pedregosa et al., 2011).
- Variance Ratio Criterion (VRC) that quantifies the ratio of "between-cluster dispersion" and "within-cluster dispersion". The higher the VRC, the better the cluster is (Zhang and Li, 2013).

We compute the performances of all the optimal clusters for the initial dataset and reconstructed datasets. To this end, we utilize SSE, DB, and VRC for K-means, TS-Kmean and TS-Kshape, and only DB and VRC for HDBSCAN, as the latter doesn't have the SSE object in Python.

5 RECONSTRUCTED DATASETS WITH AUTOENCODERS

Since numerous services run on the servers' side, data are generated at high speed and with soaring dimensionality. Consequently, we adopt two self-supervised deep-learning methods to improve the data quality: Deep AutoEncoder (DAE) and Convolutional AutoEncoder (ConAE). AutoEncoders uses encoder and decoder layers. The former uses a latent space to compress the inputs, and the later reconstructs the original dataset as closely as possible from this compressed data(Wang et al., 2016). Autoencoders learn from the data while back-propagating the neural network by disregarding insignificant data during encoding, resulting in a better-reconstructed dataset (Lawton, 2020). Furthermore, the goal of training AutoEncoders is to minimize the reconstruction loss; the lower the reconstruction loss, the more similar the reconstruction of the original data can be generated (Wang et al., 2016). Thanks to these methods, we do not worry about reducing the high feature space optimally.

The main challenge is determining the optimal architecture for our complex service monitoring dataset. We first develop the DAE using a deep, fully connected neural network. We try several rigorous combinations of hidden layers, loss function, weight optimizer, activation functions, epochs and batch sizes.



(a)

```
Epoch 1/50
53953/53953 [==============================] - 37s 691us/sample - loss: -0.2580
Epoch 2/50
53953/53953 [==============================] - 38s 699us/sample - loss: -0.7693
Epoch 3/50
53953/53953 [==============================] - 40s 744us/sample - loss: -0.8844
Epoch 4/50
53953/53953 [==============================] - 37s 692us/sample - loss: -0.9619
```

(b)

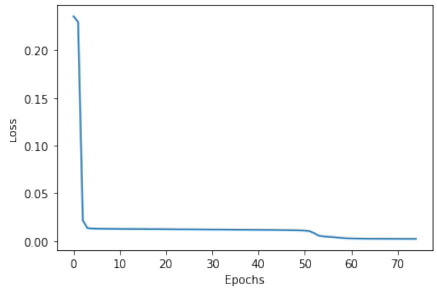
Figure 4: Loss for Different Combinations of DAE.

For instance, if we utilize 10 hidden layers for both encoder and decoder, MSE as the loss function, Adam as the optimizer, Relu as the activation function, batch size of 256 with 3500 epochs, the obtained loss is high (more than 0.45) as shown in Figure 4 (a). On the other hand, if we use only one hidden layer for both encoder and decoder, SGD as the optimizer, Sigmoid as the activation function, batch size of 512 with 50 epochs, we obtain a negative loss as depicted in Figure 4 (b).

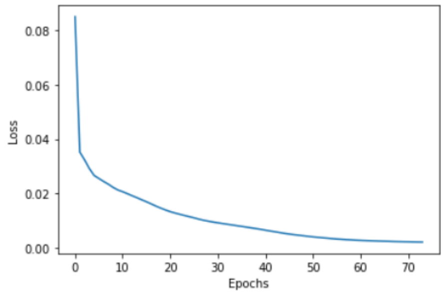
The best architecture that we attain for DAE comprises 6 hidden layers for both encoder and decoder, 1032 for batch size, Adadelta as the optimizer, Relu for all the hidden layers, Sigmoid for the output layer as activation function, and MSE as the loss function. More precisely, for the encoder part, we sequentially provide 3100 (original), 2500, 1650, 1032, 500, 100 and 5 features using six hidden layers, and again, we reconstruct the features from 5, 100, 500, 1032, 1650, 2500 and 3100.

Regarding ConAE, we build a sequential neural network with two hidden layers for both encoder and decoder. For the encoder layers, we utilize the Conv1D class with 128 and 16 filters, and for the decoder layers, Conv1D with 16 and 128 filters; the kernel size of all the filters is 3. For the encoding layers, we use MaxPooling1D with a pool size of 2 to downsample the input representation. We adopt UpSampling1D with size of 2 for the decoder to upsample the input representation from the encoder. Also, keep in mind that the output of ConAE is a 3D array; hence, it needs to be converted to a 2D array before using it for subsequent experiments.

Besides, we use five consecutive epochs with no reduction by 0.0001 as the stopping criterion for training, and the reconstruction error for DAE is 0.0016 with the 75th epoch out of 100 epochs. However,



(a)



(b)

Figure 5: Loss Graph for DAE (a) and ConAE (b).

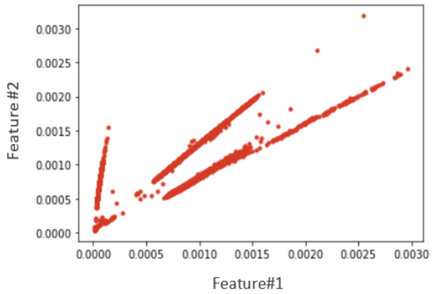


Figure 6: Reconstructed Dataset using DAE.

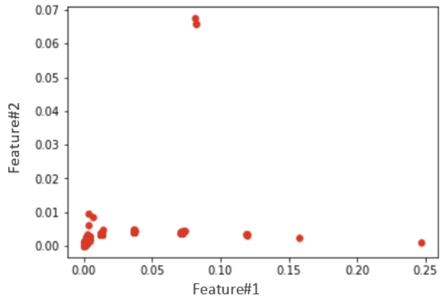


Figure 7: Reconstructed Dataset using ConAE.

while implementing ConAE, the critical challenge is the computational complexity. Thus, instead of 5 consecutive epochs, we choose 3 without reducing loss by 0.0001 as the stopping criterion. We obtain the reconstruction error of 0.0021 and optimal epoch of 74. Here, for both DAE and ConAE, the iterations stop at 75th and 74th epochs respectively as they meet the stopping criterion. We present the loss graphs for DAE and ConAE in Figure 5 where the loss curve goes steep down drastically after three epochs for DAE in Figure 5(a) and gradually goes down for ConAE in Figure 5(b). Furthermore, Figures 6 and 7 illustrate the reconstructed datasets with the first two features that we obtain after utilizing DAE and ConAE models. In Figure 6, data are scattered across the distribution, and in contrast, in Figure 7, data are more densely located in similar positions.

Nevertheless, one crucial question raises while compressing the initial dataset with DAE and ConAE is that how much information was lost. For this purpose, we employ the reconstruction error to measure the information loss. As mentioned earlier, we obtain the reconstruction error of 0.0016 and 0.0021, respectively, for the reconstructed datasets using DAE and ConAE, which are very minimal. Hence, we can conclude that with deep-learning methods, we lost a very minimum amount of information.

6 CLUSTERING QUALITY OF INITIAL DATASET

First, we utilize Elbow method, Silhouette coefficient and CH Index to search for the best number of clusters for the initial dataset, as presented in Table 2, and Elbow, Silhouette and CH Index are described below:

1. Elbow method: One of the most popular techniques for identifying the optimal number of clusters. It is based on the calculation of "Within-Cluster-Sum of Squared (WSS)" errors for a different number of clusters (k). It iterates over the k and calculates the WSS errors (Yuan and Yang, 2019). Small values indicate that clusters are more likely to be convergent, and after reaching the optimal cluster's number, WSS error starts declining (Yuan and Yang, 2019).

2. Silhouette coefficient: This metric calculates the cluster's cohesion and separation (Pedregosa et al., 2011). It measures how well an instance fits into its corresponding cluster. The values of the Silhouette coefficient range between -1 and 1 (Pedregosa et al., 2011). A high (close to 1) silhouette score indicates that data are closer to their assigned clusters than others. A score close to 0 means that data is very close to or on the decision boundary between two neighboring clusters. A score close to -1 means that data is probably as-

Table 2: Optimal Cluster Numbers.

Dataset	Optimal Clustering		
Initial Dataset	**Elbow**	**Silhouette**	**CH**
	5	5	4
Reconstructed Dataset with DAE	**Elbow**	**Silhouette**	**CH**
	5	6	14
Reconstructed Dataset with ConAE	**Elbow**	**Silhouette**	**CH**
	5	5	5

signed to a wrong cluster (Kaoungku et al., 2018).

3. CH Index: The basic idea of CH index is that clusters that are very compact and well-separated from each other are good clusters. This index is a metric that compares how similar a cluster's instance is to that than other clusters (Wang and Xu, 2019).

Then, we fed the optimal number of clusters from Table 2 to the three clustering methods (K-means, TS-Kmeans and TS-Kshape). We do not supply the number of clusters to HDBSCAN, as by default it produces this number (which is 6). We report the performances of the four clustering methods in Table 3, with a tally of 20 results. We attain the minimum SSE (0.004348) with TS-Kshape using 5 clusters, the minimum DB (0.61332) with K-means using 4 clusters. K-means with 4 clusters provides the maximum VRC (103431.341). However, the data performance with HDBSCAN is not satisfactory. Due to the high data density, we present the 3-D visualization of two examples of optimal clusters in Figure 8 to have a much better graphical representation where x, y ans z axes represent the first three dimensions: dimension#1, dimension#2, and dimension#3.

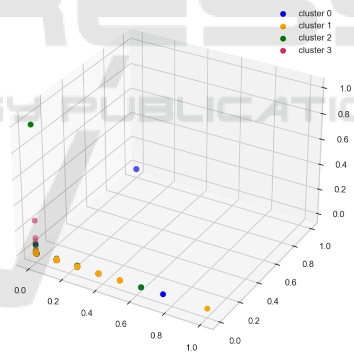
Table 3: Optimal Clustering Quality of Initial Dataset.

K-means					
5 clusters			**4 clusters**		
SSE	DB	VRC	SSE	DB	VRC
245568.441	0.613830	102604.2395	313075.295	**0.61332**	**103431.341**
TS-Kmean					
5 clusters			**4 clusters**		
SSE	DB	VRC	SSE	DB	VRC
4.9938	0.613830	102604.2395	5.80274	0.7040410	97865.0800
TS-Kshape					
5 clusters			**4 clusters**		
SSE	DB	VRC	SSE	DB	VRC
0.004348	2.243981	75912.984	0.00716	0.70334	62285.962
HDBSCAN with 6 clusters					
DB	VRC				
1.3517	80707.7806				

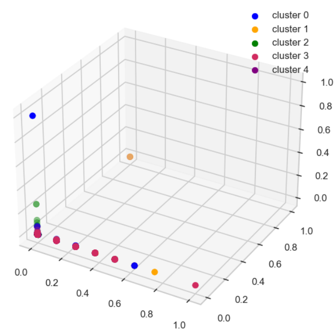
7 CLUSTERING QUALITY OF RECONSTRUCTED DATASETS

Table 2 exposes the optimal clustering for the reconstructed datasets. For the ConAE dataset, all the techniques (Elbow, Silhouette and CH) return the same number, unlike for the DAE dataset. Elbow technique yields the same optimal clustering for the three datasets. However, CH recommends different clustering numbers, especially for the DEA datasets. Most of the numbers are close by, except one (14), and among the nine results, six return the number 5. Since the reconstructed DAE dataset is sparsely separated over the feature-space, CH Index returns a higher ratio of between and within cluster sums of squares, resulting in a higher (14) optimal clustering.

Next, Table 4 evaluates the optimal cluster quality for the DEA reconstructed dataset, with a tally of 20 results. We obtain the lowest SSE of 0.0019202 with TS-Kshape using 14 clusters, the minimum DB of 0.05016857 with K-means and TS-Kmeans using 6 clusters, and the highest VRC of 30,312,918.2572 with K-means using 14 clusters. A higher VRC score implies that the clusters are dense (minimized intra-cluster distance) and well separated (maximized inter-cluster distance) (Pedregosa et al., 2011). Table 5 assesses the quality of the ConAE reconstructed dataset. The lowest SSE of 0.004682736 is achieved with TS-Kshape, the minimum DB with of 0.61332691 with both K-means and TS-Kmean, and the highest VRC of 95738.59064 with K-means. Across the three datasets, HDBSCan under-performs.



(a) K-means with Four Clusters.



(b) TS-Kshape with Five Clusters.

Figure 8: Two Examples of Optimal Clusters of Initial Dataset.

Table 4: Quality of DAE Reconstructed Dataset.

Kmeans								
Elbow-5 clusters			**Silhouette-6 clusters**			**CH-14 clusters**		
SSE	DB	VRC	SSE	DB	VRC	SSE	DB	VRC
16807.5332	0.181151753	1510548.891	1252.5371	**0.05016857**	16349947.76	259.94039	0.5234089	**30312918.2572**
TS-Kmean								
Elbow-5 clusters			**Silhouette-6 clusters**			**CH-14 clusters**		
SSE	DB	VRC	SSE	DB	VRC	SSE	DB	VRC
0.31155592	0.18115175	1510548.89	0.023216931	**0.05016857**	16349947.76	0.00497385071	0.482265234	28591306.875589
TSKshape								
Elbow-5 clusters			**Silhouette-6 clusters**			**CH-14 clusters**		
SSE	DB	VRC	SSE	DB	VRC	SSE	DB	VRC
0.002113596	0.4164552564	50036.65944	0.0019847939	0.43711877	315043.8333	**0.0019202**	0.4703590	16066475.8277
HDBSCAN-6 clusters								
DB	VRC							
1.026604381	12825430.68							

Table 5: Quality of ConAE Reconstructed Dataset (5 Clusters).

K-means		
SSE	DB	VRC
270260.4375	**0.61332691**	**95738.59064**
TS-Kmean		
SSE	DB	VRC
6.316888253	**0.61332691**	73127.0153677
TS-Kshape		
SSE	DB	VRC
0.004682736	1.7982134	71203.693461
HDBSCAN-5 clusters		
DB	VRC	
1.18025933	76806.51995	

8 COMPARISON

Table 6 compares the clustering performances between the initial dataset and the two reconstructed datasets. All the metric results of the DAE reconstructed dataset outperform the outcome attained with the initial dataset due to the non-linear properties of the activation functions. The gap between the SSE values equals 0.0024 (minimal), between the DB values 0.56316 (high), and between VRC values 30,209,486.919 (very high).

In contrast, for the ConAE reconstructed dataset, we observe that all performance metrics are underperforming due to the convolutional layer that could not handle the non-linear time-series dataset. Nevertheless, the ConAE metrics are pretty close to the metrics obtained with the initial dataset.

In conclusion, the DEA dataset possesses the highest quality. Moreover, for the SSE metric, the TS-Kshape is the dominant clustering method across the three datasets. For the DB and VRC metrics, K-means is the most performing method. Also, 14 represents the best cluster number. For conducting the subsequent decision-making tasks, the DEA dataset based on K-means with 14 clusters will be provided to the industrial partner, as the latter provides a large gap between the VRC values. Furthermore, we visualize all the best clustering performances for the DEA reconstructed dataset in Figure 9 where each cluster orientation is different from others for TS-Kshape, TS-Kmeans and K-means.

9 CONCLUSIONS AND FUTURE WORK

Our study first constructed a high-dimensional time-series dataset. However, this new dataset should be of high quality as it will be utilized for essential decision-making tasks by the industrial partner. We jointly addressed two significant problems of this dataset: data incompleteness and high dimensionality. We thoroughly assessed the quality of the initial dataset and reconstructed datasets produced with self-supervised deep learning networks using several data clustering approaches. The experiments showed a higher quality for the reconstructed dataset with DAE when using a higher number of clusters.

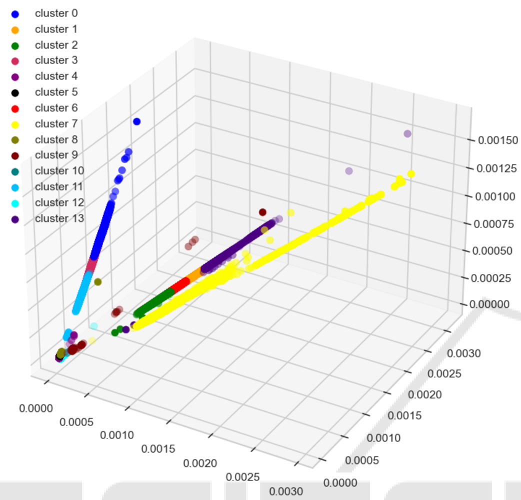
A crucial research direction of our study is to explore clustering-based outlier detection of the reconstructed datasets.

ACKNOWLEDGEMENTS

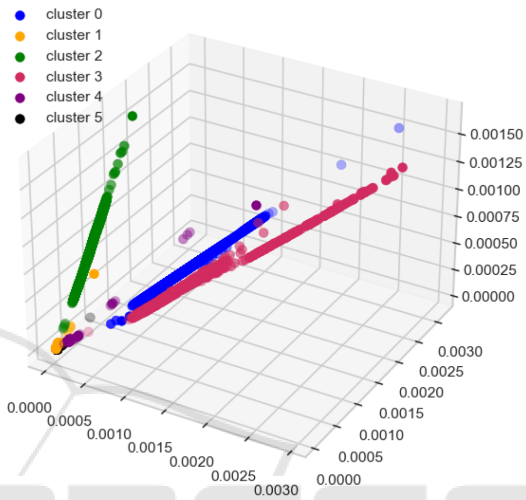
We cordially thank the Observability team for granting us access to the data.

Table 6: Comparison based on Clustering Performances.

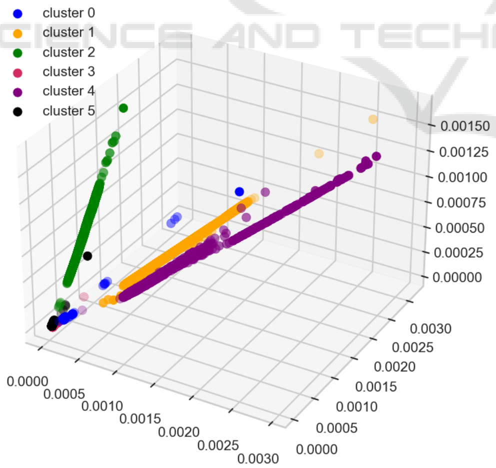
Dataset	Metric 1			Metric 2			Metric 3		
	Clustering Algo.	Cluster No.	SSE	Clustering Algo.	Cluster No.	DB	Clustering Algo.	Cluster No.	VRC
Initial	TS-Kshape	5	0.0043	K-means	4	0.61332	K-means	4	103431.341
DAE	TS-Kshape	14	**0.0019**	K-means TS-Kmean	6	**0.05016**	K-means	14	**30312918.26**
ConAE	TS-Kshape	5	0.0046	K-means TS-Kmean	5	0.61336	K-means	5	95738.59



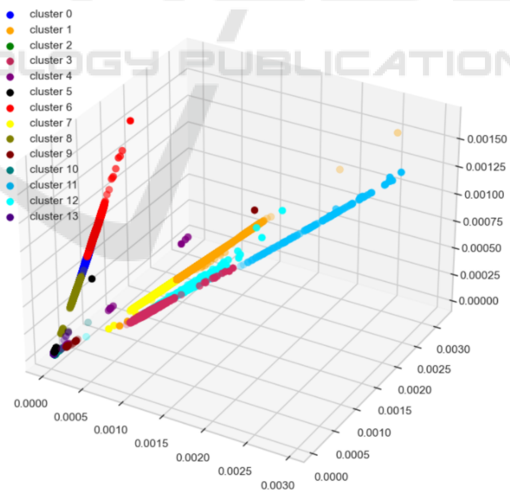
(a) TS-Kshape with 14 clusters.



(b) TS-Kmean with 6 clusters.



(c) K-means with 6 clusters.



(d) K-means with 14 clusters.

Figure 9: Optimal Clusters for DEA Reconstructed Dataset.

REFERENCES

Aghabozorgi, S., Shirkhorshidi, A. S., and Wah, T. Y. (2015). Time-series clustering–a decade review. *Information Systems*, 53:16–38.

Anowar, F. and Sadaoui, S. (2020). Incremental neural-network learning for big fraud data. In *2020 IEEE International Conference on Systems, Man, and Cybernetics (SMC)*, pages 3551–3557.

Anowar, F. and Sadaoui, S. (2021a). Incremental learning framework for real-world fraud detection environment. *Computational Intelligence*, 37(1):635–656.

Anowar, F. and Sadaoui, S. (2021b). Incremental learning with self-labeling of incoming high-dimensional data. In *The 34th Canadian Conference on Artificial Intelligence*, pages 1–12.

Anowar, F., Sadaoui, S., and Selim, B. (2021). Conceptual and empirical comparison of dimensionality reduction algorithms (pca, kpca, lda, mds, svd, lle, isomap, le, ica, t-sne). *Computer Science Review*, 40:1–13.

Chormunge, S. and Jena, S. (2018). Correlation based feature selection with clustering for high dimensional data. *Journal of Electrical Systems and Information Technology*, 5(3):542–549.

Dash, B., Mishra, D., Rath, A., and Acharya, M. (2010). A hybridized k-means clustering approach for high dimensional dataset. *International Journal of Engineering, Science and Technology*, 2(2):59–66.

Huang, X., Ye, Y., Xiong, L., Lau, R. Y., Jiang, N., and Wang, S. (2016). Time series k-means: A new k-means type smooth subspace clustering for time series data. *Information Sciences*, 367:1–13.

Jadhav, A., Pramod, D., and Ramanathan, K. (2019). Comparison of performance of data imputation methods for numeric dataset. *Applied Artificial Intelligence*, 33(10):913–933.

Jindal, P. and Kumar, D. (2017). A review on dimensionality reduction techniques. *International journal of computer applications*, 173(2):42–46.

Kaoungku, N., Suksut, K., Chanklan, R., Kerdprasop, K., and Kerdrasop, N. (2018). The silhouette width criterion for clustering and association mining to select image features. *International journal of machine learning and computing*, 8(1):1–5.

Lawton, G. (2020). Autoencoders' example uses augment data for machine learning. https://searchenterpriseai.techtarget.com/feature/Autoencoders-example-uses-augment-data-for-machine-learning. Last accessed 15 November 2021.

McInnes, L. and Healy, J. (2017). Accelerated hierarchical density based clustering. In *2017 IEEE International Conference on Data Mining Workshops (ICDMW)*, pages 33–42. IEEE.

Messaoud, T. A., Smiti, A., and Louati, A. (2019). A novel density-based clustering approach for outlier detection in high-dimensional data. In *International Conference on Hybrid Artificial Intelligence Systems*, pages 322–331. Springer.

Niennattrakul, V. and Ratanamahatana, C. A. (2007). On clustering multimedia time series data using k-means and dynamic time warping. In *2007 International Conference on Multimedia and Ubiquitous Engineering (MUE'07)*, pages 733–738. IEEE.

Paparrizos, J. and Gravano, L. (2015). k-shape: Efficient and accurate clustering of time series. In *2015 ACM SIGMOD International Conference on Management of Data*, pages 1855–1870.

Pedregosa, F., Varoquaux, G., Gramfort, A., Michel, V., Thirion, B., Grisel, O., Blondel, M., Prettenhofer, P., Weiss, R., Dubourg, V., Vanderplas, J., Passos, A., Cournapeau, D., Brucher, M., Perrot, M., and Duchesnay, E. (2011). Scikit-learn: Machine learning in Python. *Journal of Machine Learning Research*, 12:2825–2830.

Prabhu, P. and Anbazhagan, N. (2011). Improving the performance of k-means clustering for high dimensional data set. *International journal on computer science and engineering*, 3(6):2317–2322.

Prometheus (2021). From metrics to insight. https://prometheus.io/docs/concepts/metric_types/. Last accessed 15 November 2021.

Rani, S. and Sikka, G. (2012). Recent techniques of clustering of time series data: a survey. *International Journal of Computer Applications*, 52(15):1–9.

Saul, N. (2017). How hdbscan works. https://hdbscan.readthedocs.io/en/latest/how_hdbscan_works.html. Last accessed 15 November 2021.

Song, Q., Ni, J., and Wang, G. (2011). A fast clustering-based feature subset selection algorithm for high-dimensional data. *IEEE transactions on knowledge and data engineering*, 25(1):1–14.

Stekhoven, D. J. and Bühlmann, P. (2012). Missforest—non-parametric missing value imputation for mixed-type data. *Bioinformatics*, 28(1):112–118.

Tavenard, R., Faouzi, J., Vandewiele, G., Divo, F., Androz, G., Holtz, C., Payne, M., Yurchak, R., Rußwurm, M., Kolar, K., et al. (2020). Tslearn, a machine learning toolkit for time series data. *Journal of Machine Learning Research*, 21(118):1–6.

Wang, X. and Xu, Y. (2019). An improved index for clustering validation based on silhouette index and calinski-harabasz index. *IOP Conference Series: Materials Science and Engineering*, 569(5):1–7.

Wang, Y., Yao, H., and Zhao, S. (2016). Auto-encoder based dimensionality reduction. *Neurocomputing*, 184:232–242.

Wu, W., Xu, Z., Kou, G., and Shi, Y. (2020). Decision-making support for the evaluation of clustering algorithms based on mcdm. *Complexity*, 2020:1–17.

Yuan, C. and Yang, H. (2019). Research on k-value selection method of k-means clustering algorithm. *J*, 2(2):226–235.

Zhang, Y. and Li, D. (2013). Cluster analysis by variance ratio criterion and firefly algorithm. *International Journal of Digital Content Technology and its Applications*, 7(3):689–697.