An Ensemble-based Dimensionality Reduction for Service Monitoring Time-series

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Keywords: Service Monitoring, High-dimensional Time-series, Dimensionality Reduction, Incremental Dimensionality Reduction, Clustering Quality, Data Reconstruction.

Abstract: Our work introduces an ensemble-based dimensionality reduction approach to efficiently address the high dimensionality of an industrial unlabeled time-series dataset, intending to produce robust data labels. The ensemble comprises a self-supervised learning method to improve data quality, an unsupervised dimensionality reduction to lower the ample feature space, and a chunk-based incremental dimensionality reduction to further increase confidence in data labels. Since the time-series dataset is massive, we divide it into several chunks and evaluate each chunk's quality using time-series clustering method and metrics. The experiments reveal that clustering performances increased significantly for all the chunks after performing the ensemble approach.

1 INTRODUCTION

In industry, an incredible amount of data is produced daily, and in many applications, data need to be processed and analyzed in real-time. Even though machine learning algorithms can handle a vast quantity of data, their performances worsen as the feature space becomes larger (Van Der Maaten et al., 2009), (Spruyt, 2014). The predictive models become more complex as the dataset's size and dimensionality increase (Verleysen and François, 2005), (Jindal and Kumar, 2017). Decision models trained on a large feature space become reliant on the data and may over-fit (Hawkins, 2004), (Anowar et al., 2021). Additionally, the models' accuracy declines due to the presence of similar or irrelevant features (Jindal and Kumar, 2017). This problems get worse when high-dimensional time-series data is produced. Regular machine learning algorithms cannot handle the continuous time-series data (Losing et al., 2018). Our study emphasizes an industrial application on service availability, which allows users to check what our servers are up to. Hence, data are crawled continuously or periodically with higher data dimensionality for monitoring services' availability. A robust Service Monitoring dataset was developed in (Anowar et al., 2022), which is temporal, unlabeled, and highly dimensional.

Furthermore, many machine learning methods fail to perform efficiently in real-world scenarios because of having inadequate target labels. Hence, it is crucial achieving the highest confidence for the class labels. For this purpose, we introduce an ensemble-based dimensionality reduction approach to efficiently process an industrial use case's high dimensional, nonlinear, and unlabeled time-series dataset with two objectives: 1) to better the data quality and 2) to produce highly confident data labels. For the experimental purpose, we have taken the new Service Monitoring dataset from (Anowar et al., 2022), and we partition the dataset into six week-by-week chunks.

The ensemble approach combines four methods to handle this particular time-series dataset: a self-supervised learning method, an unsupervised dimensionality reduction, an incremental dimensionality reduction, and a time-series clustering. As a self-supervised method, we adopt Autoencoder to reconstruct the chunks in better data spaces by ignoring disturbances, such as noisy and insignificant data. Subsequently, we utilize the Kernel PCA (KPCA), an unsupervised dimensionality reduction method, to reduce the ample feature spaces of the reconstructed chunks into much shorter representations. Fewer dimensions mean less computation, faster training, easier data visualization, and less storage. The ulti-

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Anowar, F., Sadaoui, S. and Dalal, H.
An Ensemble-based Dimensionality Reduction for Service Monitoring Time-series.
DOI: 10.5220/0011273700003277
In *Proceedings of the 3rd International Conference on Deep Learning Theory and Applications (DeLTA 2022)*, pages 117-124
ISBN: 978-989-758-584-5; ISSN: 2184-9277

mate goal of this research is to obtain the highest level of confidence in the data labels for the Service Monitoring dataset. For this purpose, we employ a chunk-based incremental KPCA, an unsupervised incremental dimensionality reduction method proposed in (Tokumoto and Ozawa, 2011). We apply the incremental learning method to each of the previously reduced chunks to improve the clustering performance so that the cluster's labels are accurate. We utilize the cluster's labels as the target data labels. We do not consider the incremental KPCA to reduce the dimensionality of the chunks; instead, we improve the data quality.

To the best of our knowledge, there are minimal incremental dimensionality reduction methods available for the supervised setting in the literature. This limitation is even worse when dealing with non-linear and unlabeled data (i.e., unsupervised). The chunk-based incremental KPCA proposed in (Tokumoto and Ozawa, 2011) is the only incremental dimensionality reduction method that is chunk-based as opposed to the instance-based incremental dimensionality reduction methods, and this is why we choose it.

Experimental results disclose that we obtain high clustering performances with the ensemble-based chunks. The latter outperforms the performances of the initial chunks in all cases. Better clustering performances ensure that the clusters are of better quality where intra-cluster distances are maximized and inter-cluster distances are minimized. In addition to that, we will attain higher confidence in the target labels for the further decision-making task for the industrial partner.

We organize our paper as follows. Section 2 discusses recent literature on the efficacy of Incremental KPCA. Section 3 summarizes the characteristics of the Service Monitoring dataset and then divides it into multiple weekly chunks. Section 4 details the proposed ensemble-based dimensionality reduction framework to produce accurate data labels. Section 5 presents the experiments to assess the effectiveness of the ensemble method in terms of clusters' quality. Section 6 concludes our study and highlights some future works.

2 RELATED WORKS

The very few incremental, unsupervised dimensionality reduction techniques have been defined in (Kim et al., 2005), (Chin and Suter, 2007), (Takeuchi et al., 2007), (Tokumoto and Ozawa, 2011). However, most of them are instance-based where incoming data are processed instance by instance. One of the very first Incremental KPCA was proposed in (Kim et al., 2005), which is based on the 'Generalized Hebbian Algorithm' presented as an online algorithm for linear PCA in (Sanger, 1989), (Oja, 1992). The hybrid algorithm iteratively estimates the kernel principal components using only a linear order memory complexity, which makes it suitable for large datasets. However, until an adequate accuracy is achieved, this Incremental KPCA necessitates a high number of learning iterations.

(Chin and Suter, 2007) developed an incremental KPCA that is based on the incremental linear PCA introduced in (Lim et al., 2004). The Eigen-feature space is incrementally updated instance by instance in this proposed Incremental KPCA by performing Singular Value Decomposition on the incoming training data. However, the Eigen-space model is updated without learning all of the training data repeatedly, this approach can be called a one-pass incremental learning algorithm. Furthermore, higher memory and computation costs are required to construct a reduced dataset. The time and memory complexities are $O(n^3)$ and $O(n^2)$, respectively for this algorithm.

The study (Takeuchi et al., 2007) proposed an incremental KPCA where an eigen-feature space is represented by a combination of linearly independent data, allowing it to learn from new data incrementally without having to remember previous training data. However, an open problem remains in this proposed algorithm, is that an eigen-feature space should be updated by solving an eigen value problem only when new training data is received, which means that eigen-value decomposition should perform for each data in the chunk individually to update the eigen-feature space, which leads to higher time and memory complexity, and it can only update eigen-vectors quickly with a small set of linearly independent data (lower dimensionality). Additionally, if the chunk size is larger, real-time online feature extraction may be impossible.

Later, the research (Tokumoto and Ozawa, 2011) proposed a chunk-based incremental KPCA that conducts the Eigen-feature space learning by only executing the Eigen value decomposition once for each chunk of incoming training data. The cumulative proportion is used to choose linearly independent data whenever a new chunk of training data becomes available. Then, the Eigen-space augmentation is performed by measuring the coefficients for the chosen linearly independent data, and the Eigen-feature space is rotated based on the rotation matrix generated by solving a kernel Eigen value problem. So far, this proposed chunk-based algorithm is the most efficient Incremental KPCA.

The authors in (Joseph et al., 2016) proposed an incremental KPCA by extending the algorithm defined in (Takeuchi et al., 2007) to make it work for the chunk setting. In this incremental KPCA, first, a chunk of data is split into several smaller chunks since author considered that retaining a suitable size of data chunk is vital for fast learning. Then, from the divided data chunks, only important features are selected using regular KPCA, because not all data in a chunk are valuable for learning. In the proposed incremental KPCA, an Eigen-feature space is spanned by Eigen vectors that are presented by a linear combination of independent data. Later, a rotation matrix to update the Eigen vectors and an Eigen value matrix is attained by solving an Eigen value decomposition problem only once for given data chunk. However, reducing a chunk twice and keeping only few data from a chunk is not practical always when processing real-world dataset like time-series.

3 AN INDUSTRIAL TIME-SERIES DATASET

Our past study (Anowar et al., 2022) developed a Service Monitoring time-series, a new highly dimensional and unlabeled dataset derived from an industrial application, so developers can monitor service availability, react to changes in service-wide performance, and optimize service allocation. The dataset was constructed from 48 sub-servers that used Prometheus to collect data every 15 seconds for various services for over six weeks in the year 2020. The chunks, containing information over six weeks (39 days), come in different sizes and feature sets. A dataset sample denotes the service's availability, UP or DOWN, for a given point of time. For example, one instance may show that the service is up at 12.01 a.m., while another instance may suggest that the service is down at 5.00 a.m. The Service Monitoring data can be of two types: 1) Counter type indicating a monotonically growing counter whose value can either increase or be reset to zero on the restart, and 2) Gauge type denoting a single numerical value that can arbitrarily go up and down (Anowar et al., 2022). A detailed description of this dataset is provided in past work (Anowar et al., 2022).

The Service Monitoring dataset is large, comprising 53,953 data and 3100 features. Hence, it requires enormous memory space to be processed, particularly when performing the KPCA method. The latter necessitates a sizeable short-term memory to perform the kernel function and store the large kernel matrix to project data to higher feature space so that data can be linearly processed (Goel and Vishwakarma, 2016). Hence, it is impossible to perform the kernel on the whole dataset. Therefore, we split the dataset into six chunks, one chunk for each week. This split enables processing chunks in an incremental manner.

The first chunk possesses 9,099 data, the sixth chunk has 4,534 data, and the four others have 10,080 data. These chunks have the same size because they have the same amount of time for seven days, starting at midnight and ending at 11.59 pm. The data collection for the first day of the first week began at 4.21 pm, and the last week has only four days. Table 1 presents the size and dimensionality for each chunk.

Table 1: Size and Dimensionality of Weekly Chunks.

Chunk	Size	Dimensionality
#1	9,099	3,100
#2	10,080	3,100
#3	10,080	3,100
#4	10,080	3,100
#5	10,080	3,100
#6	4,534	3,100

4 ENSEMBLE-BASED DIMENSIONALITY REDUCTION

When data come with high dimensionality, the training process for machine learning algorithms becomes difficult, resulting in over-fitting the decision models and lowering their performances (Jindal and Kumar, 2017). These problems are even worse when processing complex data like time series. To this end, we propose an ensemble-based dimensionality reduction approach to manage unlabeled, non-linear, and high-dimensional time-series chunks, intending to improve each chunk's quality and increase its labeling confidence.

We first utilize a self-supervised learning method on each time-series chunk to reconstruct its data and improve its quality. Then, we adopt an unsupervised dimensionality reduction technique to efficiently reduce the ample feature space. The reduced chunk is then passed to an incremental, unsupervised dimensionality reduction method not to lower the dimensionality but to improve the data quality further and increase the chunk labels' confidence. Lastly, we assess the quality of the final chunks by checking their clustering performances to decide on the cluster labels and show the necessity of our approach. The following section describes each phase of the ensemble-based dimensionality reduction approach.

4.1 Data Reconstruction of Each Chunk

We adopt a deep autoencoder model (named DAE) as a pre-processing phase to increase data quality by removing noisy data without changing the feature space. Besides, DAE can process non-linear data, like ours, efficiently by adopting non-linear activation functions in hidden and output layers (Almotiri et al., 2017). DAE consists of two parts: 1) the encoder compresses the input data to a smaller encoding with a latent space, and 2) the decoder reconstructs the compressed data as closely as possible (Wang et al., 2016). DAE learns from data when backpropagating through the neural network and excluding irrelevant discrepancies during encoding, resulting in an accurately reconstructed dataset (Lawton, 2020). The DAE aims to minimize the reconstruction loss; the smaller the loss, the reconstructed data is more likely to be the original data (Wang et al., 2016). We first train DAE with the whole time-series dataset to tune the hyper-parameters (hidden layers, weight optimizer, loss function, batch size, epoch number, and stopping criterion) and also determine the optimal architecture. This DEA configuration will be utilized for each weekly chunk.

4.2 Dimensionality Reduction of Each Chunk

We make use of the popular feature extraction technique KPCA to manage each available chunk. The KPCA method uses the “kernel trick” to project data into a higher feature space so that data can be linearly separable (Hoffmann, 2007). We employ RBF as the kernel function for KPCA to better handle the non-linearity of data. PCA uses the Eigen decomposition to produce the Eigen vectors and values (Fan et al., 2014). The Eigen vectors represent the new obtained features called Principal Components (PCs).

Before applying KPCA, we search for the best number of PCs by maximizing the “Total Explained Variance Ratio” metric (TEVR) to ensure no significant lose of information after reconstructing a chunk. TEVR accumulates the explained variances of all the PCs. The explained variance of a PC represents the overall information contained by the PC (Kumar, 2020).

4.3 Incremental Dimensionality Reduction of Each Chunk

Our objective is to perform the incremental KPCA on each chunk to improve the clustering performances and achieve the most confident cluster labels. We adopt the chunk-based incremental KPCA algorithm introduced in (Tokumoto and Ozawa, 2011) and discussed in Section 2 (related work). This study (Tokumoto and Ozawa, 2011) provided only the theoretical framework. Another work (Hallgren and Northrop, 2018) implemented this sophisticated algorithm, which is capable of handling the training chunks sequentially.

No direct library or package is available for incremental KPCA in Python, Matlab, or R programming languages. To use the incremental KPCA in Jupyter Notebook, we first clone a Git repository from Github where the implementation of the chunk-based incremental KPCA (Hallgren and Northrop, 2018) was provided. For using this Git repository efficiently, Python 3.6 or higher versions, Numpy, and Scipy must be installed. The Git module must be placed in the same folder as the Python script to invoke the incremental KPCA algorithm. Moreover, the input data must be passed as an array for this implementation. Additionally, to extract the desired principal components, we have to conduct the dot product of the input data matrix with the updated Eigen vectors returned from the incremental KPCA program each time separately for all the chunks. Moreover, unlike conventional KPCA implementations, this method returns all the Eigen vectors (PCs) in decreasing order, allowing users to select the desired PCs (the new features).

4.4 Clustering Evaluation of Each Chunk

We employ a time-series clustering algorithm for each ensemble chunk to produce the clusters. We utilize the TS-Kshape method since Service Monitoring dataset is temporal. TS-KShape is a domain-independent and shape-based time-series clustering technique (Paparrizos and Gravano, 2015). In each iteration, TS-Kshape provides the similarity between two time-series data based on the normalized cross-correlation to update the cluster assignments (Paparrizos and Gravano, 2015). To efficiently determine the centroid of each cluster, TS-Kshape considers the centroid computation as an optimization problem by minimizing the sum of the squared distances to all the other data points from the centroid.

In addition, we consider two as the cluster number since the Service Monitoring dataset will have two target labels (Up and Down). We evaluate the cluster quality of the ensemble chunks using two performance metrics: Davies-Bouldin (named DB) Index and the Variance Ratio Criterion (named VRC). The DB Index calculates how similar each cluster is on average, implying that the intra-cluster distance should be kept to a minimum, and VRC is a criterion that returns the ratio of between-cluster and within-cluster dispersion (Pedregosa et al., 2011), (Zhang and Li, 2013). The lower, the better for DB Index, and the higher, the better for VRC (Pedregosa et al., 2011).

5 EXPERIMENTS

5.1 Autoencoder Configuration

To find the optimal architecture for DAE, we perform grid search over multiple hyper-parameters. The best DEA architecture is composed of six hidden layers for both encoder and decoder, 1032 for batch size, Adadelta for the weight optimization, Relu activation function for all the hidden layers, Sigmoid function for the output layer, and MSE for the loss function. For the encoder part, we sequentially provide 3100 (original), 2500, 1650, 1032, 500, 100 and 5 features using the six hidden layers, and again, we reconstruct the features from 5, 100, 500, 1032, 1650,2500 and 3100. We utilize five epochs with no reduction in the reconstruction loss by 0.0001 as the stopping criterion for training. We use this optimal DAE configuration for each incoming chunk individually.

5.2 First Chunk Transformation

We first describe the entire transformation process on chunk #1 to improve the understandability. We train the optimal DAE configuration on the first chunk until the model's loss is not converging anymore, intending to build the best-reconstructed data. After reconstruction, the chunk will have the same dimensionality as the initial one but with much better data quality. The maximum TEVR and optimal PCs for chunk#1 are 0.999920 and 75, respectively. We, therefore, utilize 75 PCs when executing the KPCA algorithm to reduce the dimension space and the incremental KPCA algorithm to produce better quality of data.

We note that the chunks obtained after utilizing DAE+KPCA are denoted as "reduced chunks", and after applying chunk-based incremental KPCA they are named "ensemble chunks". From Table 2, we observe that the reduced chunk (DAE+KPCA) outperforms the initial chunk with a large margin. The initial chunk has DB and VRC of 1.552 and 3,455.962, respectively, whereas the reduced chunk returns DB of 0.5248 and VRC of 4,352.035. After utilizing the incremental KPCA, we achieve much better DB for chunk#1, though VRC under-performs with a tiny gap.

After utilizing the chunk-based incremental KPCA, we have one metric (DB) outperforming and one metric slightly underperforming for chunk#1. Hence, it is vital to decide which (reduced or ensemble) chunk to use for the next decision-making task, such as chunk labeling. For this purpose, we illustrate the initial, reduced, and ensemble representations of chunk#1 in Figure 1 to decide which chunk to utilize. From Figure 1-(a, b), we observe that the two clusters are very closely located. If two centroids are very close, then there could be a possibility that an instance can be mis-clustered, whereas, in 1-(c), two clusters are sparsely located and can be differentiated easily. Hence, we choose the ensemble chunk over the reduced one for chunk#1. Also, we will select the ensemble chunk when a similar scenario happens between reduced and ensemble representations for the subsequent chunks.

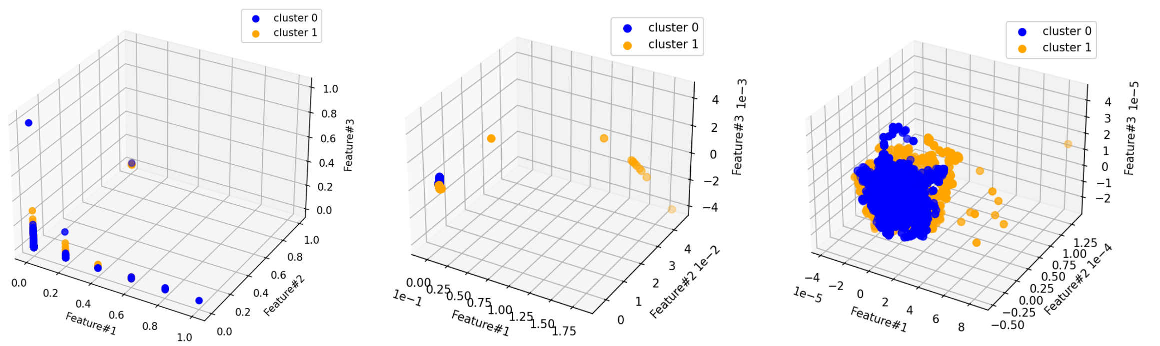
Table 2: Cluster Performances of Chunk#1.

TEVR (in %)		**Optimal PCs**
99.9920		75
Chunk	**DB**	**VRC**
Initial	1.552	3,455.962
Reduced	0.5248	**4,352.035**
Ensemble	**0.5238**	4,321.608

5.3 Remaining Chunks Transformation

By maximizing the TEVR metric for each chunk individually, we acquire the optimal PCs that is used for the feature reduction method KPCA. Thus, we ensure that the obtained PCs for a chunk hold most of the information from its initial representation, and also the same number of PCs is used with the chunk-based incremental KPCA to improve the data quality. For instance, for chunk#2, we attain the count of PCs of 100 with the maximum TEVR of 99.8900%.

Table 3 exposes the clustering quality for each weekly chunk in terms of DB and VRC metrics between the initial and ensemble chunks. We perform TS-Kshape clustering technique with two clusters on all the chunks. We can see that the cluster quality has improved significantly with a large gap for both metrics for all the chunks after applying the ensemble-based dimensionality reduction approach. For example, with the the initial data of chunk#3, DB and VRC are 0.4546 and 1,499.436, respectively, whereas, the ensemble chunk produced DB and VRC of 0.0851 and 447,828.401, respectively.



(a) Initial Chunk. (b) Reduced Chunk. (c) Ensemble Chunk.

Figure 1: First Chunk: Comparison of Initial and Transformed Chunks.

Table 3: Clustering Performances of Remaining Chunks.

Chunk	TEVR	PCs	Initial		Ensemble	
			DB	VRC	DB	VRC
#2	99.8900	100	0.7446	17,361.61	**0.5424**	**24,166.550**
#3	99.9998	117	0.4546	1,499.436	**0.0851**	**447,828.401**
#4	99.9992	76	0.5948	22,167.308	**0.0807**	**882,006.425**
#5	99.9000	100	5.6940	1,110.825	**0.6086**	**14,621.410**
#6	99.9100	120	3.256	388.953	**0.6528**	**6,654.930**

Next, in Table 4, we also compare the clustering performances of the reduced and ensemble chunks for the remaining weeks of data. We notice that the cluster quality has improved significantly for the ensemble chunks in most cases, particularly for chunks#3, #4, and #5. Also, chunk#6 outperforms for VRC using the ensemble-based dimensionality reduction. However, ensemble chunk#2 under-performs for both metrics compared to the reduced chunk#2. The differences between reduced and ensemble chunks are the following:

- For chunk#3, #4, and #5, the ensemble-based chunks outperform with a huge gap in terms of VRC, whereas, DB outperform with a small gap.
- For chunk#6, only one metric outperforms. VRC increased with a medium gap for chunk#6 compared to the reduced chunk.
- The ensemble-based dimensionality reduction under-performs for chunk#2 compared to the reduced chunk#2, but with a small and medium gaps for DB and VRC, respectively.

5.4 Data Labeling

Table 5 presents the number of instances for the two clusters for the initial and ensemble chunks. As an example, regarding chunk#1, out of 9099 instances, we have 4315 and 4784 instances for clusters 0 and 1, respectively. On the other hand, we have 3733 and 5366 instances for clusters 0 and 1, respectively, for the ensemble-based initial chunk. Since the ensemble-based dimensionality reduction approach provided superior clustering performances for most chunks, we intend to use its cluster labels as the data labels for all the chunks.

We also show the mismatch between initial and ensemble clusters in Table 5. For instance, for chunk #1, we have 1164 instances from the ensemble chunk that do not belong to the same cluster as the initial chunk. We attain the highest mismatch of 1530 instances for chunk #5. For chunk#4, both initial and ensemble chunks have exact instances for the two clusters. Moreover, the class distribution is moderately balanced for all the chunks using the ensemble-based dimensionality reduction method. The highest imbalance ratio is ≈ 1:3 for chunk #3.

In the future, we will pass only the mismatched instances of chunk#1 to the human experts to analyze them and provide us with the ground truth. The first chunk will be used to build the initial classification model for service monitoring. Based on an incremental learning approach introduced in (Anowar and Sadaoui, 2021), we will develop the decision model gradually using the chunks' labels.

Table 4: Clustering Performances of Reduced and Ensemble Chunks.

Chunk	Reduced		Ensemble	
	DB	VRC	DB	VRC
#2	**0.5147**	**25,727.25**	0.5424	24,166.550
#3	0.0906	395,121.06	**0.0851**	**447,828.401**
#4	0.0808	881,211.368	**0.0807**	**882,006.425**
#5	0.6126	14,294.565	**0.6086**	**14,621.410**
#6	**0.6420**	6,631.924	0.6528	**6,654.930**

Table 5: Instances in Each Cluster for Each Weekly Chunk.

Chunk	Initial		Ensemble		Mismatch
	Cluster 0	Cluster 1	Cluster 0	Cluster 1	
#1	4315	4784	3733	5366	1164
#2	4144	5936	4310	5770	332
#3	2299	7781	2313	7767	28
#4	4525	5555	4525	5555	0
#5	4791	5289	5556	4524	1530
#6	2702	1832	2306	2228	792

6 CONCLUSIONS AND FUTURE WORKS

Service monitoring is vital because it allows users to make proactive decisions when problems arise by fixing issues and reducing server downtime. The proposed framework addressed the problems of real-world data: unlabeled, non-linear and high dimensional time-series data. Nevertheless, service monitoring applications generate time-series data with a soaring feature space. For this purpose, we devised an ensemble-based dimensionality reduction approach based on 1) self-supervised learning to better data quality, 2) unsupervised dimensionality reduction to reduce the high data dimensionality, and 3) incremental dimensionality reduction to improve data labeling.

While implementing this ensemble approach, we also verified that a minimal amount of information was lost throughout the reduction process of the feature space. We further utilized a time-series data clustering method to assess and compare the quality of the initial, reduced, and ensemble chunks. The experimental results showed that higher-quality clusters (maximum intra-cluster and minimum inter-cluster distances) had been attained using the ensemble approach. These high-performing clusters and cluster labels will be utilized for subsequent decision-making tasks for the industrial partner.

This current work leads to other research directions for the same industrial application, as follows:

- Based on the data labels obtained in this study, we will devise an adaptive ensemble learning approach to update gradually the service monitoring classifier with incoming chunks.
- We are also interested in incorporating the clustering-based outlier detection methods within the ensemble-based dimensionality reduction approach to remove outliers from the data.

ACKNOWLEDGEMENTS

We want to express our gratitude to Global AI Accelerator (GAIA) Ericsson, Montreal for collaborating with us on this research work, the Observability team for allowing us to access the data, and Fredrik Hallgren, University College London, UK, for providing us with the partial implementation of Incremental KPCA.

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