A Probabilistic Approach for Data Management in Pervasive Computing Applications

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Abstract—Current advances in Pervasive Computing (PC) involve the adoption of the huge infrastructures of the Internet of Things (IoT) and the Edge Computing (EC). Both, IoT and EC, can support innovative applications around end users to facilitate their activities. Such applications are built upon the collected data and the appropriate processing demanded in the form of requests. To limit the latency, instead of relying on Cloud for data storage and processing, the research community provides a number of models for data management at the EC. Requests, usually defined in the form of tasks or queries, demand the processing of specific data. A model for pre-processing the data preparing them and detecting their statistics before requests arrive is necessary. In this paper, we propose a promising and easy to implement scheme for selecting the appropriate host of the incoming data based on a probabilistic approach. Our aim is to store similar data in the same distributed datasets to have, beforehand, knowledge on their statistics while keeping their solidity at high levels. As solidity, we consider the limited statistical deviation of data, thus, we can support the storage of highly correlated data in the same dataset. Additionally, we propose an aggregation mechanism for outliers detection applied just after the arrival of data. Outliers are transferred to Cloud for further processing. When data are accepted to be locally stored, we propose a model for selecting the appropriate datasets where they will be replicated for building a fault tolerant system. We analytically describe our model and evaluate it through extensive simulations presenting its pros and cons.

Index Terms—Pervasive Computing, Internet of Things, Edge Computing, Data Storage, Accuracy, Probabilistic Model

I. INTRODUCTION

The combination of the Internet of Things (IoT) and Edge Computing (EC) provides a promising infrastructure for supporting innovative Pervasive Computing (PC) applications. The aim of PC is to offer ambient intelligence to end users having devices and services interacting with them. IoT devices are, usually, carried by end users or they are present in the environment in close distance with them facilitating the envisioned interactions and the collection of data. Then, data become the subject of processing activities to create knowledge and support novel applications. At the EC, we can detect numerous nodes that are, in an upwards mode, connected with Cloud for transferring data and ask for more advanced processing. A new trend is the collection and storage of data at the EC to eliminate the latency in the provision of responses in various requests (instead of always relying on Cloud). EC nodes have direct connection with IoT devices and become the hosts of a high number of geo-distributed datasets. Obviously, as new data arrive, one can observe the ‘evolution’ of the local datasets as depicted by their statistics. This evolution is represented by updates in the statistical information, e.g., the mean and standard deviation may be altered as new information is retrieved by the IoT devices.

Users/applications perform requests upon the distributed datasets to create knowledge or ask for analytics. Requests can have the form of tasks (e.g., apply a machine learning model and report the outcome) or queries (e.g., report the list of data that meet a specific condition). When a request is set, the ‘base case’ model is to launch it across the network and search the information that end users/applications are interested in [29]. However, this involves an increased messaging overhead paid without any reason for nodes/datasets that do not match to the desired conditions set by the request. The most efficient solution is to have a view, beforehand, on the statistics of the available data and decide upon the matching between the requests and the distributed datasets. Through this approach, we can eliminate the cost of allocating tasks/queries to datasets that do not match to the defined conditions as their execution will return an empty set. A number of research efforts propose techniques for the optimal tasks/queries allocation into a number of processing nodes, e.g., [13], [15], [18], [19], [21], [22], [23].

Another challenge is to keep the consistency and accuracy of data at high levels as the critical statistical information that depicts the quality of the collected data [8]. Accuracy refers to the closeness of estimates to the (unknown) exact or true values [32], i.e., it depicts the error between the observation and the real data. Envision a new data vector arriving from an IoT device to an EC node. The discussed vector may affect the accuracy of the local dataset as it may not match to dataset’s current statistics (e.g., it may be an outlier to the specific dataset). We borrow the concept of ‘solidity’ to represent the closeness of data into a dataset [20] and adopt it to build a model for the efficient allocation of data to the appropriate datasets. A solid dataset exhibits a high accuracy realized when the error/difference between the involved data is low, e.g., the standard deviation may be limited. We have to notice that accuracy is significant as efficient response plans,
for each type of tasks/queries, may be defined. Apart from maintaining the solidity of datasets, we have to focus on data replication to support a fault tolerant EC infrastructure. Such an approach will provide benefits when connectivity is limited and data can be processed to deliver the required responses. In the discussed ecosystem, there is no need for additional data migration that will burden the network. It is preferable to migrate tasks/queries instead of circulating huge volumes of data. Replication in combination with the distributed data storage may assist in the elimination of the probability of data loss and cope with IoT nodes failure as well [1].

This paper targets to support the distributed nature of the EC ecosystem and the provision of an ensemble model for outliers detection combined with methodologies for the selection of the appropriate datasets where new data vectors should be stored. EC nodes adopt a monitoring scheme for examining the incoming data and a decision making model for performing the envisioned allocations. For outliers detection, we rely on simple, however, fast ensemble approach extending our previous efforts in the domain [25]. Instead of adopting an individual majority voting method upon multiple outlier indicators, we study a double majority scheme to conclude if the incoming data are outliers. Furthermore, when data are not considered as outliers, we study the time series of difference ‘quanta’, i.e., the time series of the difference between the incoming data and the synopses of the available datasets as reported by EC nodes. We consider that nodes at pre-defined epochs share the synopses of their datasets to become the basis for the proposed replication process. Evidently, these quanta show the statistical ‘behaviour’ of data synopses exhibiting the trends in every dataset. The new data are placed at the datasets where the similarity with the synopses is high, i.e., the difference quanta are limited. In any case, our replication model is based on historical quanta realizations instead of relying to the latest one. Compared with our previous efforts [20], [25], the proposed model exhibits the following differences: (i) we provide an aggregation mechanism for the management of multiple outlier indicators upon multiple datasets instead of using a limited number of indicator functions like in [20], [25]. The proposed scheme can be applied upon any number and any type of indicators; (ii) for the replication process, we rely on a probabilistic approach upon multiple historical quanta instead of using an uncertainty driven model [20]. The adoption of the uncertainty management scheme requires the manual definition of a rule base which is not necessary in the current model. The following list reports on the contributions of our paper:

- we provide an ensemble model for the aggregation of multiple outlier indicators upon a double majority voting scheme;
- we support the data replication process with a probabilistic model based on multiple historical synopses reported by EC nodes. Our aim is to detect the similarity of the incoming data with the available datasets upon their past trends;
- we present the outcomes of an extensive set of experiments to reveal the characteristics of the proposed approach.

The paper is organized as follows. Section II reports on the related work in the domain. In Section III we present the preliminary information while in Section IV we provide the analytical description of our model. In Section V we present our experimental evaluation and in Section VI we conclude our paper by providing our future research directions.

II. RELATED WORK

Outliers detection and management is a widely studied research domain. The interested reader can refer in [41] for an extensive survey for getting insights on the proposed methodologies. These methods target to identify objects deviating from a group of other objects. Deviating objects depict an abnormal behaviour compared to the natural evolution of the collected data. If we compare univariate with multivariate data, one can argue that the latter scenario is more prone to outliers, i.e., the effects of outliers in the statistics of data have higher impact than in the former case [33]. Recall that in the vast majority of the application domains, data are reported in a multivariate ‘form’, i.e., tuples/vectors making the detection of outliers a difficult task [27]. For detecting outliers, we have to rely on statistical metrics like the covariance matrix [14]. Mahalanobis distance is the most representative metric that builds upon the covariance matrix adopted to detect the correlations between the multiple dimensions of data vectors [30]. Other techniques involve the Cook’s distance [9] and the leverage model [2]. The former metric estimates variations in regression coefficients after removing each observation, one by one. The latter model performs in a similar way to the Mahalanobis distance as it is based on the study of residuals and their distance from the mean vector. Additional techniques can be found in the relevant literature like the $\chi^2$ metric for identifying deviations from the multidimensional normality.

An extension of the Mahalanobis distance is proposed in [27], i.e., a variant based on the minimum covariance determinant, a more robust process that is easy to implement. In [3], the interested reader can find a comparison of outlier detection methods.

Data replication is usually adopted to achieve two goals, i.e., the minimization of the latency in the provision of responses and the support of fault tolerant systems. In the first axis, we avoid data or requests migration while in the second axis, we are able to perform the desired processing even if a node is not available. The replication of data is a technique adopted in Wireless Sensor Networks (WSNs) where we need to upload IoT data from a set of sensor gateways on distributed Cloud storage [26]. In this scenario, we can consider multiple mini-Clouds as the hosts of data taking replication requirements for each data item into account. A distributed algorithm for the replication placement is proposed in [40]. The authors propose the use of distributed storages and a method for improving the efficiency of objects replication. The main subject of [39] is the reliability assessment of clustered and declustered replica...
placements. In [4], the authors present a self managed key-value store which dynamically allocates the resources of a data Cloud to several applications, thus, it maintains differentiated availability guarantee for different application requirements.

Other efforts formulate the problem around what, when and where data replication should take place [11]. Such a modelling can assist in applying optimization schemes for concluding the best possible action. Data replication may also assist in eliminating the need for migrating huge volumes of data as bulk data transfer protocols aim to do [56]. We can perform a selective replication under constraints avoiding to circulate all the collected data in the network. Such a selective approach can be realized online [57], however, under the goal of choosing the appropriate hosts to have data close to the appropriate users. In networks, where nodes exhibit limited energy resources, we have to balance the number of replicas to the energy consumption [5]. We can achieve the discussed goal adopting compression and reduction techniques before the replication takes place. This step may be adopted in the pre-processing stage where data are pre-processed before sending them to the storage node to reduce the energy consumption without affecting the data quality requirements [6]. The disadvantage of the discussed approaches is that they require a complex process and increased computational resources for compression/decompression. Modelling the energy footprint of nodes may be also adopted to create replication plans that aim to reduce the energy consumption [38]. In [28], the authors incorporate a load balancing approach when performing the desired replication process. They assume that every node has a local memory adopted to store neighbour nodes memory contents. ProFlex [31] is proposed to deal with the communication requirements for transferring data from ‘weak’ to strong nodes. TinyDSM [34] exhibits a reactive replication method that distributes replicas based on a random strategy according to the number and the density of replications. Finally, in [35], the authors propose a low-complexity distributed mechanism to increase the capacity of WSN-based distributed storage, optimizing communication and decreasing energy usage. Data are collected periodically by the sink node being removed from nodes’ memories while, based on a greedy distribution storage scheme, each node reports its memory condition to other nodes.

III. PROBLEM DESCRIPTION & PRELIMINARIES

The problem under consideration involves a set of IoT devices reporting data to an EC node being member of a group of N nodes, i.e., \( n_1, n_2, \ldots, n_N \). EC nodes receive the data and perform an initial pre-processing for deciding their storage or rejection. A rejection corresponds to the transfer of data to Cloud while a decision related to storage fires another round of processing to deliver the appropriate node where the incoming data should be replicated. EC nodes formulate local datasets, i.e., \( \{ D_1, D_2, \ldots, D_N \} \) upon which they perform the requested processing activities. The discussed datasets are updated upon the arrival of new multivariate data vectors, i.e., \( x = [x_1, x_2, \ldots, x_M] \). Additionally, due to the proposed replication process, data vectors can be exchanged by peer nodes as the result of the proposed decision mechanism. \( D_i \)s exhibit specific statistical information and data synopses can be extracted upon them to be disseminated in peers for supporting the envisioned decision making. For instance, the synopsis for the \( i \)th dataset can refer in a vectorial space via a \( M \)-dimensional vector, i.e., \( s_i = [s_{i1}, s_{i2}, \ldots, s_{iM}] \) conveying statistical information for each of the adopted \( M \) dimensions. Synopses may represent linear multivariate regression coefficients, clusters centroids (in a clustering scheme), the first Principal Components (PCs) (in linear data compression) or very simple statistical measures like the mean or standard deviation. We target to keep EC nodes informed about the data present to their peers, thus, support decision making upon fresh information for the collected data. Obviously, there is a trade off between the frequent data synopses calculation in the burden of network performance (a high number of messages is required to transfer synopses to peers) compared to a less frequent synopses extraction in the burden of decision making upon ‘obsolete’ data synopses. The study of the discussed trade off is beyond the scope of this paper.

Initially, every node \( n_i \) should detect if \( x \) is an outlier not only compared with the local dataset \( D_i \) but also with the remaining repositories present at peer nodes. Our aim is to detect if \( x \) significantly deviates from the ‘ecosystem’ of datasets, thus, no dataset could become the host of \( x \). For this, we rely on an ensemble approach and study the involvement of multiple outlier detection methods. \( x \) is rejected when multiple indicators depict an outlier judgement in multiple datasets. The discussed synopses ‘participate’ in the delivery of the outlier indication as represented by the indicators outcome. We consider that \( V \) outliers indicator functions are available, i.e.,

\[
I_j(x) = \begin{cases} 1 & \text{if } x \text{ is an outlier with probability } \beta_j \\ 0 & \text{Otherwise} \end{cases}
\]

for all \( j \in \{ 1, 2, \ldots, V \} \).

Having calculated \( V \) indicators for a dataset \( D_i \), we propose a consensus model for deciding if \( x \) is an outlier or not. Our aim is to check if \( x \) is an outlier for a high number of datasets, thus, it significantly deviates from the data ecosystem currently present at the EC. The final decision is based on a double majority voting model, i.e., an ensemble scheme taking into consideration not only an individual dataset by the entire ecosystem. When \( x \) is not an outlier, \( x \) is stored to the node \( n_i \), where it is initially reported, if it is highly correlated with \( D_i \). Apart from the local dataset, it should be also replicated to peers exhibiting a significant correlation with \( x \). The correlation is detected upon the latest \( W \) synopses reports and the similarity between them and \( x \). We define the concept of the similarity quantum, i.e., the magnitude of the similarity (as exposed by the numeric difference) between \( x \) and every synopsis reported by peers. Upon the latest \( W \) similarity/difference quanta, we expose their distribution and deliver the probability of having quanta upon a threshold. This
probability is adopted to rank the available datasets and decide where x will be replicated.

IV. THE PROPOSED MECHANISM

A. Probabilistic Outliers Detection

The preliminaries section defines the basis for our outliers detection model upon V outliers detection schemes and N datasets. We focus on the ‘collection’ of our indicators and define a two-dimensional matrix I, i.e.,

\[ I_{ij}(x) = \begin{cases} 1 & \text{if } x \text{ is outlier with probability } \beta_{ij} \\ 0 & \text{Otherwise} \end{cases} \]

I is realized upon the immediate processing of x and the available synopses and becomes the basis for the subsequent decision making. Every \( I_{ij} \) can be the outcome of any outliers detection technique (e.g., \( \chi^2 \), Grubb’s test, clustering based) depending on the type of synopsis received by peers. The simplest outliers detection technique is based on the identification of x as being ‘produced’ by the distributions depicted by the statistics of every dataset \( D_i \) [25]. Let this probability be \( P(x, D_i) \). In the group of N EC nodes, we can consider \( N \times M \) distributions, i.e., an individual distribution for each dimension of x. Let \( \Theta_{ij}, i = 1, 2, \ldots, N \& j = 1, 2, \ldots, M \) represent every distribution for the \( j \)th dimension in \( D_i \) with a probability density function (pdf) \( f_{\Theta_{ij}}(x) \). Hence, \( P(x, D_i) \) can be defined as follows: \( P(x, D_i) = \prod_{j=1}^{M} f_{\Theta_{ij}}(x) \). Given the distributions \( \Theta_{ij} \) and constant weights \( w_i > 0 \), the pdf of the mixture is \( f_{\Theta_{ij}}(x) = \sum_{v_i} w_i \prod_{j} f_{\Theta_{ij}} \).

In general, I is a matrix hosting the outcomes of \( V \times N \) Bernoulli trials with different success probabilities. Our aim, before we decide that x is an outlier, is to detect if multiple indicators agree upon this event for multiple datasets. Actually, we want to perform a double majority voting, i.e., the first per column (multiple indicators for the same dataset) and the second per row (multiple indicators for the same dataset) and perform a double majority voting, i.e., the first per column (multiple indicators for the same dataset) and the second per row (multiple aggregated indicators for the ecosystem of datasets). For the envisioned double majority voting, we adopt the \( \delta \)-majority function upon V binary variables [10]. \( \delta \) is the threshold over which we consider x as an outlier for a specific dataset. The following equation holds true:

\[ B(I_{ij}, j) = 1 \iff \sum_{i=1}^{V} I_{ij} \geq \delta \] (1)

where \( B(\cdot) \) is the indicators aggregation function. In the above equation, we can also incorporate the confidence that an outlier detectors has on the reported result. This way, we focus on a ‘fuzzy’ outliers detection methodology that apart from the binary indication, every detector reports a real value which is the probability of x to be an outlier or not. In that case, the final outcome is delivered by the following equation

\[ B(I_{ij}, j) = 1 \iff \sum_{i=1}^{V} w_i I_{ij} \geq \delta \] where \( w_i \) is the probability/confidence reported by the ith detector. The second axis of aggregation is performed upon the \( B(I_{ij}, j) = B_j \) realizations. Again, a \( \delta \)-majority function is adopted, i.e.,

\[ B'(B) = 1 \iff \sum_{j=1}^{N} B_j \geq \delta'(2) \]

where \( \delta \) is the threshold over which we consider \( x \) as an outlier or not.

As I is the set of \( V \times N \) Bernoulli trials with different success probabilities, we can easily deliver the final success probability for any incoming data vector. The sum of the outcomes of the aforementioned Bernoulli trials can be defined to adopt the variable \( Z = \sum_{i=1}^{V} \sum_{j=1}^{N} I_{ij} \) which follows a Poisson Binomial distribution with probability mass function (pmf)

\[ P(Z = z) = \sum_{A \in \mathcal{F}_m} \prod_{i \in A} \beta_{ij} \prod_{j \in A^c} (1 - \beta_{ij}) \] (3)

with \( A \) being the set of all subsets of \( m \) node indexes selected from \{1, 2, \ldots, N\} and \( A^c \) is the complement of the set \( A \). When all \( \beta_{ij} \)'s are identical, \( Z \) follows the binomial distribution. Now, we can easily define the success probability that \( x \) will be identified as outlier in the entire group of detectors and nodes. Initially, we have: The following equation holds true [25]:

\[ F(z) = \sum_{m=z}^{N} \left\{ \sum_{A \in \mathcal{F}_m} \prod_{i \in A} \beta_{ij} \prod_{j \in A^c} (1 - \beta_{ij}) \right\} \] (4)

\( F(z) \) indicates the probability of having at least \( z \) outlier identification results out of \( N \). In the above equation, the lowest value for \( z \) is

\[ z = \begin{cases} \frac{N}{2} + \frac{1}{2} & \text{if } N \text{ is even} \\ \frac{N}{2} & \text{if } N \text{ is odd} \end{cases} \] (5)

When \( N \) is high, it is not easy to calculate all the necessary subsets for \( \mathcal{F}_m \), thus, we have to rely on a computationally efficient method, i.e., on one of the methodologies presented in [10]. For instance, we could adopt an approximation model (e.g., Poisson or Normal) to quickly deliver the final probability of having \( x \) as an outlier, thus, rejected from further local processing. As far as the ‘individual’ outlier identification process concerns, we can rely on widely adopted techniques, i.e., statistical-based (parametric or non-parametric approaches), nearest neighbor-based, clustering-based, classification-based (Bayesian network-based and support vector machine-based approaches), and spectral decomposition-based approaches. The proposed model can incorporate any number of outliers detectors from the aforementioned categories.

B. Statistical Management of Data Vectors

Assume that \( x \) arrives in the EC node \( n_i \). If \( x \) is not an outlier, \( n_i \) should decide to replicate the vector in a sub-set of nodes. Our target is to apply the replication process only for nodes that are highly correlated with \( x \). The replication of \( x \) in the entire ecosystem will flood the network with messages in addition to the ‘disturbance’ of the statistics of uncorrelated
datasets ‘invited’ to host $x$. In our scheme, we select the top-$k$ similar datasets where $x$ will be replicated. The parameter $k$ is lower than $N$ to reduce any negative effects in network communications.

Our replication process is realized upon the collected synopses $s_i, \forall i$ instead of relying on a voting process adopting two correlation metrics like the model presented in [25]. In this paper, the novelty is that we detect the trend of the correlation between $x$ and the available synopses $s_i, \forall i$ estimating the unknown distribution that depicts their similarity. The latest $W$ synopses reports $\{s_i\}_{i=1}^W$ become the basis for our mechanism. We want to detect if $x$ is similar to the latest $W$ ‘views’ on each dataset. We rely on the similarity between $x$ and each $s_i$ depicted by the function $g(\cdot)$. Let $g(\cdot)$ be the distance function, i.e., $g(x, s_i) = \|x - s_i\|$. For instance, if synopses are depicted by the mean of each dimension, $g(\cdot)$ can represent the like the $L_p$ norm, $p = 1, 2, \ldots \infty$ with the $x$. When $s_i$ is depicted by the centroids of a set of clusters, $g(\cdot)$ can be the distance with the closest centroid or the accumulated distance with the set of the reported centroids. For simplicity in our notation, we consider $g_l$ as the distance calculated by $g(x, s_i)$.

Based on the collected synopses, we can have a time series of distances for $x$, i.e., $g^t_l, t = 1, 2, \ldots, W$. Upon these distances, we can expose their unknown pdf targeting to extract the probability of having the similarity between $x$ and $s_i$ upon a pre-defined threshold. We rely on the widely known Kernel density Estimation (KDE) [2] to derive the pdf of $g_l$. Based on $g^t_l$, we estimate $F_G(g_l)$ via estimating the pdf $f_G(g_l)$. Having $W$ recent samples for $g_l$, $f_G(g_l)$ is estimated as $f_G(g_l, W) = \frac{1}{W \cdot h} \sum_{t=1}^W K\left(\frac{|g_l - g_i^{W-t+1}|}{h}\right)$, where $h > 0$ is the bandwidth of the symmetric kernel function $K(u)$ (integrating to unity). One of the most frequent adopted kernel function is the Gaussian, i.e., $K(u) = \frac{1}{\sqrt{2\pi}} e^{-\frac{1}{2}u^2}$. For saving time and alleviate the complexity of the proposed model, we rely on an incremental estimation of $f_G n$. The pdf $f_G(g_l, t)$ for $t = 1, \ldots, W$ is incrementally estimated by its previous estimate $f_G(g_l, t - 1)$ and the current value $g^t_l$, that is, we recursively obtain for $t = 1, \ldots, W$ that:

$$f_G(g_l, t) = \frac{t - 1}{th} f_G(g_l, t - 1) + \frac{1}{th} K\left(\frac{|g_l - g_i^{W-t+1}|}{h}\right)$$

(6)

If we apply the Gaussian function on the KDE, we obtain an estimation of the cdf $F_G(g_l, W) = \int_{g_{\min}}^{g_l} f_G(u, W)du$ using the $W$ values $\{g_i^{W-t+1}\}_{t=1}^W$:

$$F_G(g_l, W) = \frac{1}{W} \sum_{t=1}^W \frac{1}{2} \left(1 + \text{erf}\left(\frac{g_l - g_i^{W-t+1}}{\sqrt{2}}\right)\right)$$

(7)

where $\text{erf}(\cdot)$ is the error function. Hence, at time $t$, we obtain the estimation of $\gamma_t = P(g^t_l > \epsilon) \approx 1 - F_G(\epsilon, W)$. In the first place of our future research agenda is the incorporation of an estimation model for multiple time steps forward than $W$ in the decision making mechanism.

After the calculation of $\gamma_t$, we rely on an ordered list of the available peer nodes. We rank peers upon their $\gamma_t$ result to conclude the optimal solution for the specific setup. The Probability Ranking Principle [17] dictates that if peers are ordered by decreasing $\gamma_t$ over the available datasets and $x$, the effectiveness of the model is the best to be gotten for those instances. From the ranked list, we select the top-$k$ outcomes and the corresponding nodes to host $x$. Every selected $n_j$ should, then, update the corresponding statistics of their datasets. We adopt a delay mechanism in the delivery of messages related to the new synopses taking into consideration the difference between the new synopsis with the previous one and the remaining time till the expiration of the pre-defined interval when nodes should report their synopses. A time optimized process for delivering synopses while delaying the final decision is studied in [24] and is not subject of the current effort.

V. Experimental Evaluation

A. Performance Metrics & Setup

The evaluation of the proposed model involves a set of experimental scenarios upon a real trace. The aim is to investigate the performance of our mechanism concerning the number of the detected outliers as well as the number of the stored data vectors that deviate from the statistics of every dataset. We also focus on the evaluation of the proposed model concerning its ability of replicating the incoming data to the appropriate datasets keeping their solidity at high levels. Our simulations involve a high number of data vectors generated in various nodes into the network. When a data vector is produced, we adopt different distributions for producing the corresponding values for each dimension. Our dataset is retrieved by [12]. It contains 9358 instances of hourly averaged responses from an array of five (5) metal oxide chemical sensors embedded in an Air Quality Chemical Multisensor Device. This device was placed in a highly polluted area in an Italian city. All values in the dataset are normalized in the unity interval.

The performance of the proposed mechanism is evaluated by a set of metrics as follows: (i) the percentage of the detected outliers $\omega$. As the adopted dataset does not contain outlier vectors, we randomly ‘produce’ fake outliers by changing the values of the dataset. The aim is to identify if the proposed ensemble outliers detection scheme is capable of rejecting vectors that may jeopardize the solidity of datasets. We have to notice that $\omega$ refers in the detection of vectors that are considered as outliers for the entire ecosystem. For this, we incorporate into our ensemble outliers detection model with following individual detection methods: (i) the probabilistic approach discussed in Section IV, i.e., we consider the probability of the incoming vector to be produced by the distribution characterizing every dimension of the available datasets; (ii) a statistical approach, i.e., we detect if the incoming vector significantly deviates from the mean of each dimension; and (iii) the $\chi^2$ metric. In our experimental evaluation, we produce a number of outliers equal to 1% of the retrieved values; (ii) the percentage of data vectors that deviate from the statistics of each dataset $\tau$. $\tau$ depicts the average number of ‘local outliers’
stored in every dataset after the application of our processing model compared to the total number of vectors. As a ‘local outlier’, we define the data vector deviating three times the standard deviation from the mean (under the assumption that data follow a Gaussian distribution). We try to detect if the proposed approach is capable of storing similar data vectors to the same datasets. When $\tau$ is high means that multiple vectors do not match with the remaining vectors in the dataset. Where $\tau \rightarrow 0$, our datasets do not contain any ‘outlier’ data; (ii) th solidity of the formulated datasets as depicted by the mean, $\omega$, and standard deviation, $\sigma$. We target to a low $\sigma$, i.e., to delive solid datasets. When $\sigma$ is low means that the datasets are concentrated around the mean, thus, we have a clear view of their dispersion. Such a result, as mentioned above, can assist in the efficient assignments of queries into the appropriate datasets. We perform a set of experiments for different $N$, $k$, $M$ and $W$ taking their values as follows: $N \in \{10, 50, 100\}$, $k \in \{2, 5\}$, $M \in \{2, 10\}$ and $W \in \{10, 50\}$. In total, we consider that 1,000 data vectors are received by the group of nodes and report our results for the aforementioned metrics.

### B. Performance Assessment

In Tables I (W = 10) & II (W = 50), we present our results for $\omega$ and $\tau$ metrics. We observe that the proposed model is capable of detecting the generated outliers ($\omega \in [0.70, 1.0]$) while keeping similar data to the same datasets especially when $N$ is low. $\omega$ is generally retrieved to be equal to unity except when the number of EC nodes is low and the number of dimensions is high. Additionally, an increased $k$ leads to an increased $\tau$ due to the fact that we replicate the incoming data vectors to multiple EC nodes. For instance, if $W = 10$, we observe that the number of ‘local outliers’ are 0.5% when $N = 10$ and reach 30% & 40% when $N = 100$. This means that in the scenario where we consider a high number of nodes, the dispersion of datasets increases. This situation is also affected by the increased number of nodes selected to replicate every accepted data vector ($k = 5$). In case where $W = 50$, we get similar results that make us understanding that the size of the adopted window for performing the KDE processing does not affect the performance of the proposed model.

In Figure 1, we provide experimental outcomes for $N = 10$ taking into consideration the mean and the standard deviation of the retrieved datasets. We conform our findings as discussed above, i.e., the number of dimensions affect the dispersion of data. We observe that $\sigma$ is low when $M$ is low as well.

| $N$ | $M = 2$ | $M = 5$ | $M = 10$ | $M = 2$ | $M = 5$ | $M = 10$ |
|-----|---------|---------|---------|---------|---------|---------|
| 10  | 1.00    | 0.005   | 0.90    | 1.00    | 0.005   | 0.85    |
| 50  | 1.00    | 0.08    | 1.00    | 1.00    | 0.10    | 1.00    |
| 100 | 1.00    | 0.10    | 1.00    | 1.00    | 0.20    | 1.00    |

We also observe the local outliers in case where multiple dimensions are adopted by our model. We conclude that the aggregation of the difference between the available synopses and data vectors when $M$ is high may jeopardise the solidity of datasets. However, the majority of $\sigma$ realizations is retrieved below the median for a high number of datasets.

| $N$ | $M = 2$ | $M = 5$ | $M = 10$ | $M = 2$ | $M = 5$ | $M = 10$ |
|-----|---------|---------|---------|---------|---------|---------|
| 10  | 1.00    | 0.08    | 0.90    | 0.95    | 0.08    | 0.70    |
| 50  | 1.00    | 0.10    | 1.00    | 1.00    | 0.10    | 1.00    |
| 100 | 1.00    | 0.20    | 1.00    | 1.00    | 0.30    | 1.00    |

Fig. 1. Performance outcomes related to the solidity of the retrieved datasets for $N = 10$ and $k = 2$ (up: $M = 2$, down: $M = 10$)

In Figure 2, we present our performance outcomes for $N = 100$. A low $M$ leads to a very low $\sigma$. Again, an increased $M$ may lead to an increased $\sigma$ as well. Now, $\sigma$ is lower than in the previous experimental scenario when $M = 10$, however, we can observe some outlier values over the maximum $\sigma$ realization. Similar outcomes are retrieved in the scenario where $k = 5$ (see Figure 3).

The number of messages sent to the network depends on $k$. The lower the $k$ is the lower the number of the required messages. In our experiments, the total number of messages are, in average, 1980 ($k = 2$) or 4940 ($k = 5$). If we adopt the baseline model for replication purposes, i.e., we replicate every accepted data vector to the entire network, we require 9900 messages when $N = 10$ to 99000 when $n = 100$ (in average). Finally, the time required for delivering the final result (in seconds) is in the interval $[0.004, 0.0006]$ when $N \in \{10, 50, 100\}$. The lowest value in the aforementioned interval is retrieved when all the adopted parameters get their lowest realizations and the maximum value of the interval.

| $N$ | $M = 2$ | $M = 5$ | $M = 10$ |
|-----|---------|---------|---------|
| 10  | 1.00    | 0.08    | 0.90    |
| 50  | 1.00    | 0.10    | 1.00    |
| 100 | 1.00    | 0.20    | 1.00    |
corresponds to the maximum value for all parameters. The retrieved average time requirements refer in every incoming data vector and depicts the ability of the proposed mechanism to deliver the final outcome in real time. In average, our model can serve, approximately, 160 to 250 data vectors per second.

Fig. 2. Performance outcomes related to the solidity of the retrieved datasets for $N = 100$ and $k = 2$ (up: $M = 2$, down: $M = 10$)

Fig. 3. Performance outcomes related to the solidity of the retrieved datasets for $N = 100$ and $k = 5$ (up: $M = 2$, down: $M = 10$)

VI. CONCLUSION

We discuss a simple, however, efficient probabilistic model for allocating data collected by IoT nodes to a set of EC nodes. We propose the use of an ensemble model for outliers detection in the pre-processing phase and the probabilistic allocation upon data synopses reported by EC nodes. The aim is to identify the datasets that match to the incoming vectors in order to support an efficient replication process. The proposed decision making is applied upon historical synopses creating a time series of similarity/difference realizations with the incoming data vectors. This way, we are able to build a fault tolerant EC infrastructure where nodes could perform the processing of numerous tasks/queries. The proposed mechanism manages to conclude the allocation for each incoming vector in real time. This is a strategic decision as we adopt techniques that demand limited time to provide the final results. Our performance outcomes upon a real trace indicate the advantages of the proposed scheme. The outliers detection rate is optimal for the vast majority of the experimental scenarios while the solidity of the formulated datasets is kept at high levels. In the first places of our future research agenda is to incorporate a communication model between EC nodes and include the aspects of that model into the decision making process. This will increase the applicability of the proposed mechanism being aligned with real needs.

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