Failures Forecast in Monitoring Datacenter Infrastructure Through Machine Learning Techniques: A Systematic Review

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Abstract. With the trend of accelerating digital transformation processes, datacenters (DC) are gaining prominence as increasingly critical components for business success. Modern DC are complex systems. To maintain the operation with high efficiency and high availability, it is necessary to carry out detailed monitoring, which easily results in hundreds or thousands of items being monitored. Also, the large number of possible configurations is a challenge for monitoring and correcting failures on time. However, recent advances in the field of Artificial Intelligence (AI), especially in the area of Machine Learning (ML), have been generating unprecedented opportunities to improve the efficiency of the analysis of historical monitoring data, facilitating the recognition of patterns and enabling scenarios for early detection of failures. In this sense, significant research has been published discussing the applications of ML techniques in the context of DC monitoring. Based on this context, in this paper, we aim to present a systematic literature review (SLR) that helps to understand the current state and future trends of the application of ML techniques in DC monitoring, specifically those aimed at early fault detection. This SLR also aims to identify gaps for further investigations. As main results, we identified 51 papers reporting unique studies published in conferences and journals between 2009 and 2020. Most of the works (60%) were applied in supervised algorithms, in which the most used algorithm was the Random Forest (19,60%). The main types of data used were S.M.A.R.T attributes (14 papers) and log data (10 papers).

Keywords: Machine learning · Monitoring · Data center · Systematic literature review

1 Introduction

With the trend towards accelerating digital transformation processes, datacenters (DC) have gained prominence as increasingly critical components for business success. If, on the one hand, the dependence on the high availability of DCs

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has become increasingly greater, on the other hand, the complexity of these systems has also increased.

Datacenters are buildings specifically designed to host multiple servers and communication devices with common environmental requirements and physical security needs [8]. Modern DCs are complex systems composed of multiple electrical and electronic, mechanical, digital, and control subsystems. To maintain efficient and highly available operation, monitoring each subsystem sometimes results in hundreds of thousands of items being monitored. In addition, a large number of possible configurations and the interdependence of these various subsystems and their configurations, make effective and dynamic monitoring of failures difficult. This makes it difficult especially with regard to early corrective actions in the face of those that generate unavailability and consequently impact the business. Thus, developing automatic ways of detecting anomalous event sources based on either their historical behavioral analysis or run-time status is not a trivial task [43].

However, recent advances in the field of Artificial Intelligence (AI), especially in the area of Machine Learning (ML), have generated unprecedented opportunities to improve the efficiency of the analysis of historical monitoring data, facilitating the recognition of patterns and enabling scenarios of early failure detection. Based on this context, the objective of this paper is to describe a systematic literature review (SLR) that aim to understand the current state and future trends of the application of ML techniques in the monitoring of DC, which aim at the early detection of failures, in addition to identifying gaps for future investigations.

Kitchenham, Dybå, and Jørgensen proposed the use of software engineering SLR to support Evidence-based Software Engineering (EBSE) [29]. According to Kitchenham, the most common reasons for undertaking SLRs are to summarise the existing evidence concerning treatment or technology, to identify gaps in current research (proposing areas for further investigation), and to provide appropriate background to position new research activities. Additionally, according to Kitchenham, the main rationale for undertaking SLRs instead of a literature review in a traditional manner is because the first one result in a relevant scientific value. Despite a SLR requires considerably more effort than a traditional review, it has the advantage of providing information about the effects of certain events on a wide range of settings and empirical methods [28].

This trend is reflected in Gartner's forecast that AI-derived business values may reach the 3.9 trillion USD mark in 2022 [1]. Machine learning has become one of the trends for improving the impact on business operations in several segments. It has been providing real impacts such as increased efficiency and accelerated innovation.

Nevertheless, the objects of study, solutions, and implementations are diverse and there is no consensus or guideline for strategies aimed at the broad monitoring of the various DC subsystems with a focus on failure early detection. Most of the studies present strategies/solutions aimed specifically for a particular appli-

cation, for instance, storage disks such as Solid State Drives (SSDs) [5,34] and Hard Disk Drive (HDDs) [19,23,54], to name a few.

As main results, we identified that 10 of the 51 works applied the Random Forest (RF) algorithm in a supervised way. We also identified that all works focused on history data-based methods. To achieve this goal, we seek to answer the research questions identified in Sect. 2 through an SLR.

The main contributions of this work are the review of the state of the art of machine learning applications in the early detection of failures in monitoring data center infrastructures.

This work is organized as follows: In Sect. 2, we present the method of this review, identifying the research questions, the research strategy, the inclusion and exclusion criteria and procedures, the quality assessment, and the data collection. In Sect. 3 we present the results of this method, focusing on the results of the research, on the overview of the studies, and on the results of the quality assessment. In Sect. 4 we present the results and discussions. Finally, in Sect. 5 we present the conclusions and future work for this research.

2 Method

This study was conducted as a systematic literature review (SLR). The main objective of this review was to understand the state of the art and future trends in the use of machine learning techniques in the context of monitoring data center infrastructure. As a way of achieving this objective with scientific rigor, the review was structured in a three-phase process, as described by Kitchenham [28], named: Planning, Conduction and Communication.

Kitchenham [28] argued that the most common reasons for conducting an SLR are: 1) Aiming to summarise the existing evidence concerning technology or treatment, investigating the advantages and the limitations of a particular technology. 2) Aiming to identify gaps in current research and recognizing the challenges in present studies, in this way, grounding complementary research. 3) Aiming to provide an appropriate framework to ground new research activities.

These stages were carried out to identify the current state and main trends related to the theme of machine learning applications in the context of monitoring data center infrastructure. The review was carried out through the mapping of algorithms applied, architectural models, source data, and application challenges. The review process will be described in detail next.

2.1 Research Questions

As a way of identifying primary studies, this study considered the following research questions:

RQ1. What are the main characteristics of the machine learning algorithms and models that are being applied to the monitoring of data center infrastructure?

RQ2. What types of data are being used in the proposed models? (For example, sensor data, images, event logs)
RQ3. What are the main challenges in applying machine learning to data center infrastructure monitoring?
RQ4. What are the most common types of failures identified in data center infrastructure monitoring?

Regarding RQ1, about the characteristics of ML algorithms and models, we intend to analyze the main algorithms and methods applied to historical monitoring data.

2.2 Research Strategy for Primary Studies

Primary studies were selected through the Scopus repository (Elsevier)[1]. Examples of indexed sources are: ACM Digital Library at http://dl.acm.org, IEEE Xplore at http://ieeexplore.ieee.org, Science Direct at http://www.sciencedirect.com and Springer Link at http://link.springer.com.

In order to identify the largest number of works related to research questions, the defined search string was: (datacenter OR datacenters OR "data center" OR "data centers") AND "machine learning" AND (monitoring OR faut* OR fail* OR detection OR predic*).

2.3 Inclusion and Exclusion Criteria and Procedures

As proposed by Kitchenham [26] the inclusion and exclusion criteria are the basis for the selection of primary studies and must be defined in advance, to avoid bias. The review included peer-reviewed papers, which included topics related to the application of machine learning techniques applied to datacenter monitoring for early failure detection. 1) Studies on the following topics were excluded: Studies that have not clearly defined the research questions, research process and data extraction process. 2) Duplicate studies. In cases of duplicity for the same study, the most complete work was considered. 3) Studies in languages other than English.

2.4 Study Quality Assessment

All studies included were assessed using the assessment questions (QA), adapted from Dyba [18] and described as following: QA1. Does this report empirical research? Or is the report restricted to just "lessons learned" based on an expert opinion? QA2. Does the study clearly present the objectives and rationale of the research in the report? (Including why the survey was carried out) QA3. Is the description of the research context reported adequate? QA4. Does the study report clearly the results found? All studies were evaluated to answer the 5 evaluation questions according to the following scale of scores adapted from

[1] http://www.scopus.com/.

Dyba [18]: 1 - Fully meets the criteria; 0.5 - Partially meets the criteria; 0 - does not meet the criteria. Thus, the total sum of points for each study can vary between 0 (Very bad) to 7 (Very good).

2.5 Data Collect

During this phase, the data extracted from primary studies of the review were: title, keywords, authors, country of authors, year of publication, type (newspaper, conference, workshop), objective, field of application, challenges and opportunities, context (educational/industry), methodology, algorithms, types of data used, protocols, contributions, tools/infrastructure, future work and additional comments.

3 Results

This section presents the results of the literature review. The stages of conducting the review and a summary of the works that contributed to answer the research questions are also presented. At the end, the results of the quality assessment of the studies are discussed.

3.1 Search Results

The review process started with the application of the search string defined in Sect. 2 in the Scopus repository (Stage 1), which returned 446 studies. Stage 2 was carried out by analyzing the title, abstract, and keywords of each of the articles, which resulted in 53 articles. Of the 53 articles resulting from stage 2, we performed a careful reading (Stage 3) and identified that 51 papers were useful to help answer the research questions. The data extraction spreadsheet is available at https://cutt.ly/wz87CG3. The Fig. 1 presents the study selection and analysis process.

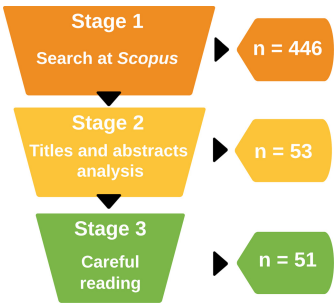

Fig. 1. Stages of the study selection and analysis process.

Table 1. 51 studies object of stage 3 - careful reading.

Id	Author	Year	Venue	Reference
T1	Zhang, J. et al.	2020	Journal	[56]
T2	Liu, C. et al.	2020	Journal	[37]
T3	Ren, H. et al.	2020	Conference	[44]
T4	Jiang, T. et al.	2020	Journal	[24]
T5	Ricci, P.P. et al.	2020	Conference	[45]
T6	Decker, L. et al.	2020	Conference	[16]
T7	Liu, X. et al.	2020	Conference	[39]
T8	Zhao, J. et al.	2020	Conference	[59]
T9	Glavan, A.F. et al.	2020	Conference	[21]
T10	Lin, F. et al.	2020	Conference	[36]
T11	Das, A. et al.	2020	Conference	[14]
T12	Shimizu, D.Y. et al.	2020	Conference	[47]
T13	Balakir, A. et al.	2020	Conference	[7]
T14	Lanciano, G. et al.	2020	Conference	[31]
T15	Kheradmandi, M. et al.	2020	Conference	[27]
T16	Zeydan, E., Arslan, S.S	2020	Conference	[54]
T17	Gao, J. et al.	2020	Journal	[20]
T18	Marahatta, A. et al.	2020	Journal	[40]
T19	Cucinotta, T. et al.	2020	Conference	[13]
T20	Alter, J. et al.	2019	Conference	[5]
T21	Zhang, J. et al.	2019	Conference	[55]
T22	Satpathi, S. et al.	2019	Journal	[46]
T23	Berezovskaya, Y. et al.	2019	Conference	[9]
T24	Huang, S. et al.	2019	Conference	[23]
T25	Borghesi, A. et al.	2019	Conference	[11]
T26	Liang, S. et al.	2019	Conference	[34]
T27	Poghosyan, A. et al.	2019	Conference	[43]
T28	Harutyunyan, A.N. et al.	2019	Journal	[22]
T29	Mozo, A. et al.	2019	Journal	[41]
T30	Diotalevi, T. et al.	2019	Conference	[17]
T31	Su, C.-J., Huang, S.-F	2018	Journal	[49]
T32	Anantharaman, P., Qiao, M., Jadav, D	2018	Conference	[6]
T33	Xiao, J. et al. et al.	2018	Conference	[51]
T34	Lin, F. et al.	2018	Conference	[35]
T35	Ahmed, J. et al.	2018	Conference	[4]
T36	Zhang, S. et al.	2018	Journal	[57]
T37	Nagashree, N. et al.	2018	Journal	[42]
T38	Adamu, H. et al.	2017	Conference	[3]
T39	Davis, N.A. et al.	2017	Conference	[15]
T40	Buda, T.S., Assem, H., Xu, L	2017	Conference	[12]
T41	Zhang, S. et al.	2017	Conference	[58]
T42	Liu, C. et al.	2017	Journal	[38]
T43	Lee, Y.-L. et al.	2017	Conference	[32]
T44	Sîrbu, A., Babaoglu, O	2016	Journal	[48]
T45	Ganguly, S. et al.	2016	Conference	[19]
T46	Yang, W. et al.	2015	Conference	[53]
T47	Bogojeska, J. et al.	2014	Conference	[10]
T48	Li, J. et al.	2014	Conference	[33]
T49	Kumar, R. et al.	2014	Conference	[30]
T50	Teixeira, P.H.D.S. et al.	2010	Conference	[50]
T51	Xu, W. et al.	2009	Conference	[52]

3.2 Overview of Studies

Considering the venue of the selected studies (journal or conference), 78.8 % were related to conferences and 21.2 % were related to journal articles. Regarding the year of publication, 37 % were published in 2020, 20.4 % in 2019, 2018, and 2017 each with 13 % with the remaining 16.6 % distributed between the years 2016 and 2009.

It is possible to notice a tendency to increase the volume of publications for selected studies on this field over the years, demonstrating a tendency to increase interest in the field of research.

3.3 Quality Assessment Results

The studies were evaluated according to the criteria defined in Sect. 2.4. The table with the detailed score of the studies is presented at https://cutt.ly/akspG0v. The studies will be referenced in this work by the ID that can be consulted in Table 1. The results demonstrate that 2 studies scored 3.5 (T6 and T8) and 49 studies reached the maximum score (5).

4 Discussions

In this section, we will discuss the answers to the research questions, as well as present the limitations and conclusions of the review.

4.1 What are the Main Characteristics of the Machine Learning Algorithms and Models that are Being Applied to the Monitoring of Datacenter Infrastructure?

In general, the analyzed researches presented a wide variety of Machine Learning (ML) strategies and algorithms applied to the monitoring of datacenter infrastructure components. In these studies, the RF algorithm was used more often (in 10 papers). The methods related to fault detection can be classified into three groups: quantitative model-based methods, qualitative model-based methods, and history data-based methods [9]. We also identified that all papers focused on history data-based methods. The ML algorithms presented in the papers were classified into three main categories: supervised, unsupervised and semi-supervised. Two studies [16] and [11] used semi-supervised algorithms. The graph presented in Fig. 2 shows the distribution of researches with a focus on each of the categories mentioned.

The supervised methods were widely applied in strategies for solving classification problems and regression problems. The main supervised algorithms were: Random Forests (RF): The algorithm has been applied to several strategies for early failure detection presenting advantages such as: having presented the best prediction accuracy, having few parameters for fine adjustments (which facilitates the training process) [5,24,39], as well as being able to handle a large

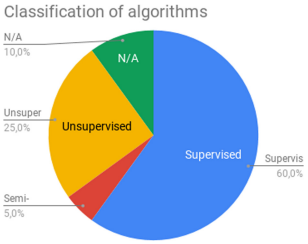

Fig. 2. Distribution of supervised and unsupervised algorithms in studies.

number of input variables without discarding these variables (facilitating the processing of multi-dimensional data) [49]. The presented disadvantage was also that of having few parameters for fine adjustments [24]. Random Forest was applied to predict disk failures in [24] and [49]. It was applied with an online approach to disk failure detection in [6] and applied to identify the remaining lifetime for Hard Disk Drives (HDDs) in [54]. There were also more extensive applications in log data in [48], in switch log data in [57] and with a focus on anticipating server failures in [39] and [32]. Other algorithms that were applied in a supervised manner were: TrAdaBoost + IMDA [56], ExtraTreeClassifier (ETC) [44], Multilayer Perceptron Networks (MPLs) [21] and [15], Ridge [9], XGBboost [12], Linear Logistic Regression [53], Gradient Boosting Machine (GBM) [10] and Parallel SVM [30], where SVM (Support Vector Machine) refers to an algorithm that can be used for classification [2]. Studies [19] (non-parametric method using decision tree) and [36] (NLP (Natural Language Processing) + GBDT (Gradient Boosted Decision Trees)) use techniques related to Decision Trees, which are essentially classifiers tree-based techniques that forecast the values using a certain number of input attributes [25]. Machine Learning algorithms with an unsupervised approach were also presented, mainly in two groups of clustering and classification problems. Regarding algorithms applied to unsupervised strategies, the main applications were based on Self-Organizing Maps(SOM) to detect anomalies based on the degradation behavior of resource consumption in the datacenter [13] and [4].

The Fig. 3 shows the main algorithms and applied techniques in the papers.

4.2 What Types of Data are Being Used in the Proposed Models? (For Example: Sensor Data, Images and Event Logs)

The researches included in this SLR are heterogeneous in terms of applications of the types of data used to train the models of failure prediction. The main types of data used as the focus of the studies were Self-Monitoring, Analysis and Reporting Technology (S.M.A.R.T) attributes (14 papers), and log data (10 papers). The S.M.A.R.T attributes refer to data collected based on the sensors of the Hard Disk Drives (HDD), such as temperature and error rates by sector.

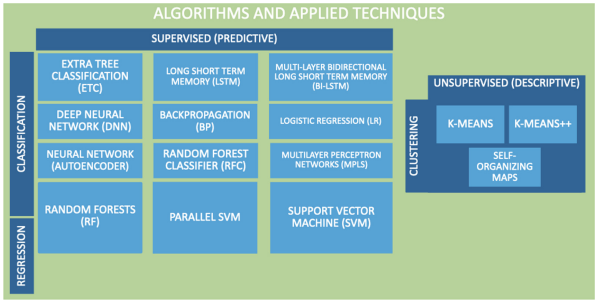

Fig. 3. Main algorithms and applied techniques.

This type of data has been widely used by HD manufacturers to determine when disk failures are likely to occur [6].

The main data sources identified in the works can be grouped into the following categories: Logs, S.M.A.R.T attributes, Performance data from CPU, Memory, I/O, Network utilization, Sensor data from hardware, and Incident tickets.

Some studies seek to identify failures in advance through logs, such as T7 that proposes a smart server crash prediction method for triggering early warning and migration in Cloud Service datacenter, [57] that seeks to determine during runtime whether a switch failure will happen soon and [48] that present a data-science study of a large amount of cluster data with the goal of building and evaluating predictive models for node failures. T6 proposes a real-time approach to monitor and classify log records based on sliding time windows and provides the basis for extracting information from log content. [14] tackles online anomaly prediction in computing systems by exploiting context-free grammar-based rapid event analysis. In [43] the authors seek to identify changes of an event source an off-line change point detection algorithm and diagnosing sick resources. [22] address several problems in intelligent log management of distributed cloud computing application and [17] implementation of a system that collects, parses, and displays the log information from specific data sources. The category S.M.A.R.T attributes refer to studies that focused on predicting failures based on historical data on health attributes of HDDs or SSDs registered by S.M.A.R.T. Performance data refers to studies that used historical performance data and its possible degradation as a mechanism for predicting failures. Hardware sensor data grouped papers that analyzed especially data collected from sensors with environmental data such as temperature and humidity. Finally, the incident tickets category refers to jobs that used metadata in incident tickets to extract the historical fault behavior and thereby make the prediction

The Fig. 4 shows the graph relating the frequency of occurrence of data types.

During the research, it was possible to notice that, in general, the studies included in this review did not demonstrate in detail the description of the tools

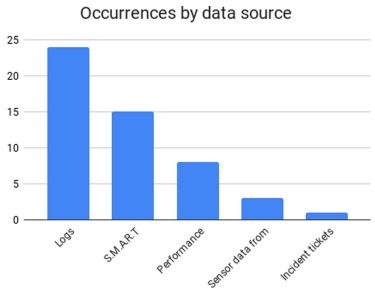

Fig. 4. Occurrences by data source.

used in the data collection stage used as a source for training machine learning models.

4.3 What are the Main Challenges in Applying Machine Learning to Datacenter Infrastructure Monitoring?

The main challenges identified in this research can be classified into the following groups:

Challenges related to Machine Learning models: ML models fail to describe the gradual change precisely [53]. Another important challenge described is called Model Aging Problem presented by [6] demonstrates that over time the data may change and the model may need to be retrained. One stable way to calibrate the model is presented in [19]. Despite the crucial role that Syslog processing plays in switch failure diagnosis, detection, or prediction, existing Syslog processing techniques have low accuracies [58].

Challenges related to complexity: An approach based on direct statistical analysis faces the challenge of the complexity of the data [5]. A large amount of information in the system log files makes it difficult to find the right pattern(s) [30]. Complexity of failure root causes [39], Complex problems can have various sources on the information Technology (IT) stack [21]. Another challenge identified was Heterogeneous minority disks [56].

Challenges related to missing data: Transient failures such as processor and memory overheating are not persistent [35], The impracticality of collecting specific service level events from inside the datacenter infrastructure [41], Lack of standard to S.M.A.R.T. data [56], and the temporary blackout of monitoring data. Also, no labels to indicate which disk was replaced [19].

The Fig. 5 summarize the main challenges identified in the works.

4.4 What are the Most Common Types of Failures Identified in Datacenter Infrastructure Monitoring?

The failures monitored in the datacenters identified in the SLR were classified in the following areas: Specific Hardware Failure, General Failure (hardware,

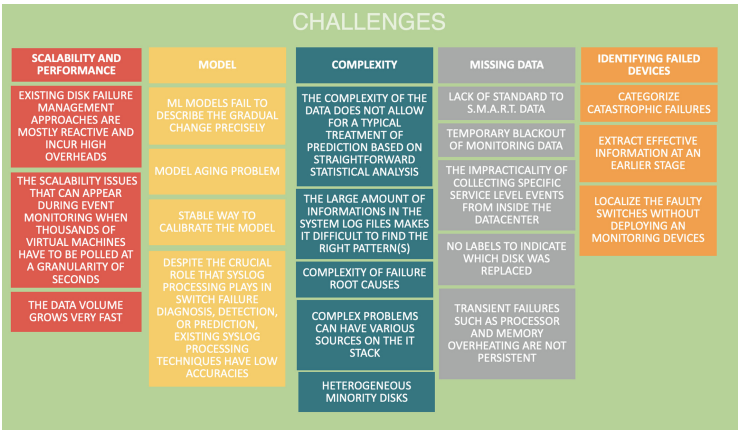

Fig. 5. Main challenges.

firmware, software, and application), Network Failure, Scheduling Failure, Software Failure, and Service Failure.

The type of failure Hardware Failure refers to studies that focused on using historical data of hardware failures as a source for predictions. General Failure refers to jobs that more broadly analyzed data such as log data, which could refer to any type of failure. The other groups were also used to group researches that focused on detecting failures based on the history of network failures, software failures, task/process scheduling (scheduling failure), and services at a higher level of abstraction (service failure).

The Fig. 6 shows the graph relating the frequency of occurrence of each type of failure in the works.

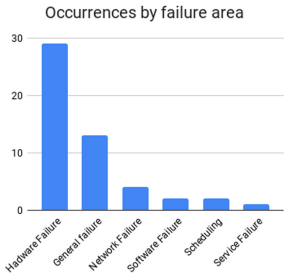

Fig. 6. Occurrences by failure area.

The most common types of failures identified during the survey were classified: General Failure (hardware, firmware, software, and application), Specific Hardware Failure, Storage disk component failure (SSDs and HDDs to name a few), Task or process execution, Network Failure, Machine or Node failure,

Service level events, Hardware Failure on Switch, Optical link failure, Software (Network Functions Virtualization - NFV and Resource Consumption) and Hardware Sensor.

4.5 Limitations of this Review

The main related limitations of this review include bias during the study selection and data extraction steps. As a way to remove the bias from these processes, we strictly followed the protocol described in Sect. 2. Another limitation of this research was the inclusion of studies in English only since publications made only in other languages may have been omitted. As a final limitation of this review, we can mention the time of conducting the review, in which some new publications may have been made and not included.

5 Conclusions and Future Work

This systematic review has discussed 51 papers reporting unique studies published in conferences and journals between 2009 and 2020. Most of the researches (60%) was applied in supervised algorithms, in which the most used algorithm was the RF (19,60%). The main types of data used were S.M.A.R.T attributes (14 papers) and log data (10 papers). The main types of failures were hardware failures. The heterogeneity of the studies concerning data sources and strategies made the data synthesis process challenging. These studies have identified an increase in interest in sustainable failure prediction strategies based on machine learning techniques. There is no consensus on the strategies to be adopted to anticipate monitoring failures in a more general way, in which the research, in general, focuses on some subsystem of the datacenter specifically. Also, it was possible to notice the lack of detailed description of the tools used for data collection in the researched papers. Based on the research we were able to identify that currently there is a growing trend towards the use of machine learning strategies applied to the monitoring of data center infrastructure through different strategies. As future work, we will use the insights identified in this review as the basis for the development of a predictive monitoring platform for the data center that will deal in particular with issues such as anticipating failure through machine learning techniques.

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