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Prescriptive Analytical Models for Dynamic IoT Data Streams: A Review

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Abstract: The application of data analysis tools and procedures to perceive value from vast volume of data created by connected IoT devices is known as IoT data analytics. While predictive analytics on IoT dealing with the prediction involved with the setting of IoT appliances, Prescriptive analytics is the next stage of IoT data analytics involves deriving actionable insights from predictions made in previous stages. The incorporation of time-dependent parameters in prescriptive models provides a more accurate depiction of a complex environment and the decision-making process that goes along with it. The scope of our work is to recommend prescriptive analytical models that make better decisions through the analysis of dynamic IoT data stream in real-time and prescribe an optimal solution. We carry out an analysis of time-series data to identify the patterns of data and learn how they change. In this direction, we attempt to represent time-series data by reducing its length, forecast change points, map change points to prescribed actions, and propose optimal decisions ahead of time events. In this paper, an overview of IoT data analytics, survey of prescriptive analytical models, applications, issues, challenges and platforms for IoT analytics are discussed.

Keywords: IoT data analytics, dynamic IoT data streams, predictive analytics, prescriptive analytics, change point detection, time-series data, optimal decision making.

1. Introduction

Internet of Things (IoT) serves as a console for several sensor devices that collaborate each other on the network, with the exchange of huge information. However, these sensors do not have the potential to perform complex data analytics computation. The major challenge relies in capturing and analysing the real time streaming of data. While the data analytics at real time is still in its inception, it requires adequate technology support for data processing and analysis [1]. The scope of our work is to recommend prescriptive analytical models that make better decisions through the analysis of dynamic IoT data stream in real-time and prescribe an optimal solution. In this direction, we attempt to represent time-series data by reducing its length, forecast change points, map change points to prescribed actions, and propose optimal decisions ahead of time events. A detailed categorization of IoT analytics is presented in Fig. 1. IoT analytics can be divided into two categories, as stated in the taxonomy of data analytics: *historical* and *proactive* analytics. Historical analytics is the classic (i.e., the most basic and widely used form of analytics) approach of obtaining visual insights from historical data mining. It can be further subdivided into descriptive and diagnostic analytics, which give visualisation or performance metrics of IoT systems and device fault notice or alerts, respectively. On the other end, proactive analytics is emerging as a new paradigm for facilitating actionable insights from huge IoT data utilising the correct data-frames.

The proactive analytics on huge IoT data may be divided into two categories: *stream IoT analytics* and *real-time IoT analytics*. While the former works with IoT data in batches or streams with no or fairly high time limitations, the later must produce an output within a stringent time limit since IoT data is delivered in small increments. Real-time analytics is quickly becoming commonplace, and it may be divided into two types: *predictive* and *prescriptive* analytics. Real-time energy usage monitoring in smart buildings to calculate clients' cost of electricity, is a typical example of predictive IoT analytics. Industrial IoT that make usage of intelligent sensors and actuators to improve industrial and manufacturing operations is an example of prescriptive analytics. Real-time IoT applications are essential for monitoring and complicated analysis [2].

A. *Relationship between IoT Analytics and Big data Analytics*

In IoT, big data analytics has grown quickly, extracting significant insights and assisting in making the best decisions under time limitations. Prescriptive analytics is in place to help businesses make automatic, reliable, time-dependent, and optimal decisions. In this direction, the

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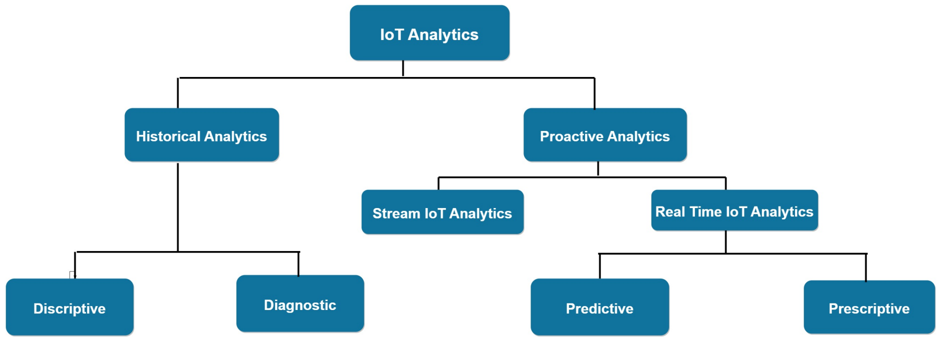

Figure 1. IoT Data Analytics Taxonomy

incorporation of time-dependent parameters in prescriptive models provides a more accurate depiction of a complex environment and the decision-making process that goes along with it. However, time-dependent parameters face substantial obstacles such as noisy data, erroneous input, and real-time data non-stationarity. As a result, learning time-dependent characteristics through sensor-driven technology is provided for prescriptive analytics, which addresses the issues posed by data uncertainty. The objective of prescriptive analytics is to gain the knowledge of predicted future and prescribe the optimised decision. It uses artificial intelligence and optimization algorithms to produce robust, automated and optimal decisions [3].

Analysing time-series data helps in detecting patterns of IoT data and changepoints that occur in data streams to map it into suitable actions. The fundamental procedure in extracting insight from time series data is dimensionality reduction. There are various methods for representing and reducing time series data such as Discrete Wavelet Transform, Discrete Fourier Transform, Piecewise Linear Segmentation, Piecewise Aggregate Approximation and so on. Different patterns within time-series data are identified based on eigen vector space model. The other major issue in the time-series analysis is to detect abrupt changes. The change point may be the changes of stationary points or some region where changes occur. There are various approaches like Cumulative Sum method, Kullback-Leibler method and Bayesian methods that are currently available for effective change point detection [4].

B. Motivation

IoT devices collect data from a variety of sources, making it even more difficult to use because combining data from diverse sources is extremely difficult. By analyzing data generated from IoT systems, IoT analytics gives a thorough solution. Prescriptive analytics, is a significant improvement in IoT analytics that enhances decision-making and process efficiency. It allows us to get much closer to correlating outcomes to particular instances. The objective of this paper is to focus on prescriptive analytics on IoT data streams since most of the papers in literature are focused on historical and predictive analytics and limited work found on prescriptive analytics with respect to IoT data streams.

C. Contributions

The rest of the paper is organised as follows: Section II covers prescriptive analytics in IoT, non-IoT and the gap between the predictive and prescriptive analytics. Section III presents issues and challenges of prescriptive analytics with respect to IoT data. A summary of prescriptive analytical approaches, models, platforms and applications in IoT are presented in section IV. Section V describes about the infrastructure required for IoT prescriptive analytics. Finally, the conclusions of the paper are presented in section IV.

2. Related Work

This section discusses the work done in both IoT and non-IoT fields related to prescriptive analytics. The research indicates that, in comparison to IoT, the majority of prescriptive analytics work is conducted in non-IoT streams. This section addresses the applications of prescriptive analytics, highlights the differences between prescriptive and predictive IoT data analytics, and gives an example of a case study.

A. Prescriptive Analytics in non-IoT

Predictive analytics describes what may occur in the future, while prescriptive analytics tells us how things ought to go. Much emphasis has been paid to prescriptive analytics in recent years in the field of business analytics and it is considered as the frontier of data analytics in the coming years. The foundation of prescriptive analytics is artificial intelligence techniques like machine learning, which refers to the capability of a computer program to understand and evolve from data without any added human input while adapting. Machine learning enables us to process a large volume of data streams. Computer programs can automatically adapt to take advantage of newly emerging information in a far more comprehensive way than any human abilities could handle.

Prescriptive analytics take advantage of the results of predictive analytics to make proactive decisions. There is a time delay between the decision and the action's execution during which the action must be prepared. Further, it should be highlighted that an action may be better done at a

TABLE I. Applications of prescriptive analytics

Application domain and References	Objective
Health care [5] [6] [7] [8] [9]	Intends to find advancements in the field of health care, with a focus on the development of prediction and optimising techniques Emphasize the importance and effective role of prescriptive analytics in achieving precision medicine, to anticipate novel COVID-19 virus and improving appointment system performance in terms of patient satisfaction and resource consumption
Resource allocation [10] [11]	Proposes an informatics system that uses predictive and prescriptive analytics to organize sales force assignments to sales opportunities to improve total revenues while retaining current selling, general, and administrative expenses
E-commerce [12] [13]	Proposes a classification model for detecting product movement on the store floor for the surveillance of electronic article and automatic checkouts. The methodology proposed here is for producing schedules for delivery by estimating the proper delivery time periods for order delivery.
Manufacturing [14]	Presents a thorough examination of important features for prescriptive analytics in manufacturing as well as the needs for a prescriptive analytics-based production control system
Maintenance [15] [16]	Proposes a methodology for optimizing the scheduling of maintenance tasks in order to increase service reliability and optimize both utilization of resources and possession periods while minimising contractual penalties and delays. Proposes a discrete-event simulation framework for describing the performance of a condition-monitoring device and then produces a suitable prescriptive maintenance approach with well-known parameters
Education [17] [18] [19] [20] [21]	Unveils a journal endorsement system that recommends a policy to improve research output by leveraging the 5W1H technique from the InSciTe system. And proposes a journal-submission method for attaining the goal of enhancing researchers' research capacities in terms of performance by taking into account their research subjects and capabilities. Proposes a model that recommends a comprehensive analytics architecture as a decision-support tool to help students with the admissions process.
Recommender system [22]	A prescriptive analytics interface for presenting and explaining temporal event sequence recommendations.
Transport [23] [24] [25] [26]	System for detection of long-range aircraft conflicts and to predict arrival time and to optimize cost index for short-haul flights is presented. A system for airline operations to predict arrival time and to optimize cost index for short-haul flights based on prescriptive analytics is proposed. Develops an optimization model that will look for a possible combination of environmental solutions that will reduce the emissions of transportation fleets. And does the evaluation of optimal solutions produced by prescriptive analytics in application like freight transportation.

specified period prior to the expected event occurring. When the event takes place, descriptive analytics is used to gain insights into what occurred and why it occurred. In this situation, descriptive analytics could be used over a longer period of time. It might manage reactive actions that happen in real-time or longer-term measures in this sense. Table I shows the list of non-IoT applications of prescriptive analytics appeared in the literature. It describes the various applications of prescriptive analytics such as healthcare, education, automobile maintenance, transportation and so on.

B. Prescriptive Analytics in IoT

The volume of IoT data is continually expanding as information and communication technology evolves. This information is generally in the form of streams. Since data samples from IoT applications are created continually at high speeds and fluctuate over time, the data is called dynamic or non-stationary. Learning from this ever-increasing volume of data necessitates flexible learning models that self-adapt over time. Prescriptive analytics is a remarkable progress in the realm of analytics. It has the potential to improve decision-making and process efficiency. It is a sub-field of Business Analytics (BA) that focuses on identifying the optimal course of action in a particular situation. In order for an IoT analytics strategy to be complete, it is required to understand importance of prescriptive analytics. It is the final stage of IoT data analytics maturity involves deriving actionable items from predictions made in previous stages. The previous descriptive, diagnostic, and predictive IoT analytics blog segments took the process one step closer to automated decision making; prescriptive analytics takes it the rest of the way. Efficient and effective decision support and/or decision automation is the culmination of a mature data analysis program. Complex systems of information that would take months of analysis to understand can be streamlined into a decision-making algorithm that runs in a fraction of a second. However, the role prescriptive analytics play in supporting decisions or automating them depends heavily on the application. The IoT environment is comprised of various subsystems. When operating on existing infrastructure, these subsystems exchange data and control the system [27]. The standard IoT architecture for big data analytics is shown in the Fig. 2. *Data source layer* consists of all sensor devices and objects that are linked over a wireless network. It is the IoT architecture's basic layer that includes hardware devices that are tied with the network layer. The two main building blocks of the IoT are Radio-Frequency Identification and Wireless Sensor Networks. The *Network layer* serves as a link between the data source layer and the analytics layer, obtaining the digital data and sending it through wired LANs, Wi-Fi, or the Internet for processing. *Analytics layer* comes next where all the data handling or data processing operations are accomplished. The final layer of the IoT analytics architecture is the *Application layer*, which leverages the data processed by the analytics layer for various applications.

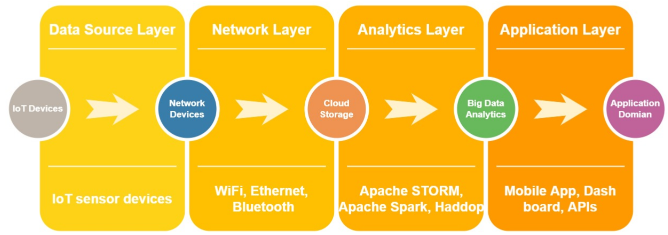

Figure 2. Layered Architecture of IoT Analytics

C. Gap between Predictive and Prescriptive IoT Data Analytics

A data strategy should include both predictive and prescriptive analytics. Predictive analytics supports in the diagnosis of prospective outcomes, Prescriptive analytics, on the other hand, investigates those possibilities and recommends the best course of action. The key distinctions between predictive and prescriptive analytics are outlined in Table II.

TABLE II. Distinctions between predictive and prescriptive analytics

Predictive Analytics	Prescriptive Analytics
What may occur in the future?	How should we act in the future?
Forecasting, Probability assessmant	Scenario based planning, Risk management, strategy formulation and simulation, Prediaction, option optimization
What-if analysis	Discrete choice modeling
Machine learning	Linear and non linear programming
Predictive modeling, Neural networks	Value analysis
Most popular and used by smaller but growing	Not yet widespread
Uses structured/unstructured data	uses knowledge base

D. Case Study

A case study illustrating the transformation of a stationary store into a smart store that tracks the products and customer behaviour is presented. The study considers RFID as a technological infrastructure for tracking products in fashion retail that uses the classification model for the detection of product movement.

As the first step, the performance characteristics of classification models are analysed that leverage low-level RFID data to distinguish between RFID-tagged items carried through an RFID gate and others. A number of common algorithms are used to approach the classification problem: logistic regression, decision trees, artificial neural networks, and support vector machines. Later it is proceeded by integrating the predictive model to optimization model to establish a prescriptive analytics model that allows for determining the respective cost impact of a particular classifier configuration and to optimize the transition detection system [12].

3. IoT Prescriptive Analytics Issues and Challenges

Many firms have widely adopted IoT and big data analytics. These technologies, however, are still in their infancy. Several current scientific issues have yet to be addressed. This section discusses numerous issues and challenges with massive IoT data analytics.

A. *Data issues*

The advancements in IoT data analytics are posed with data mining challenges like data exploration and information extraction. The high volume and data heterogeneity comprises of more ambiguity and irregular patterns that need more additional data processing steps.

1) *Volume*

The volume of data collected from differnet sensor devices may be too large to move accross the network. Dealing with such huge amount of data appears to be very challenging in IoT analytics.

2) *Accessbility*

Since the accessibility of IoT data acquired from individuals is inextricably tied to their privacy and legal rights, it is critical to comprehend how data collection, processing, and distribution can be done ethically and sustainably. As a result, in order to meet their ethical commitments, the organizations supporting IoT installations should identify and address possible human risks.

3) *Heterogeneity*

The heterogeneity in the types of devices used and the form of data generated is another issue connected with IoT data. Outside of the network, these devices come in a variety of sizes and shapes and are designed to communicate with cooperative applications. As a result, to authenticate these devices, an IoT system should assign each device a non-repudiable identifying scheme. Furthermore, for auditing purposes, businesses should keep a meta-repository of these linked devices.

4) *Data Diversity*

When data gets too big to handle, the best way to extract useful information is by dealing with the subsets of data. Those subsets have preserved all the properties of data. To train any model, system should make sure it has covered all the diverse properties of data.

5) *Data Quality*

Data quality refers to how well a data set is fit to its intended application. Various data quality attributes like accuracy, completeness, consistency, validity, uniqueness, and timeliness are ensured by analysts using data profiling and cleansing to discover and eliminate anomalies.

6) *Real Time Data*

Real-time data, also known as streaming data, is IoT data that is generated or captured in very short intervals of time and must be evaluated quickly to extract immediate insights and make quick decisions within a few hundred milliseconds to a few seconds.

B. *Visualization*

Visualization is the other significant challenge due to huge volume and high dimensionality of data. As it gives the complete interpretation of data, it is considered as one of the essential technique in data analytics. Hence, it requires a rich GUI support to get better insight from the data.

C. *Time and Location Dependencies*

Data from IoT includes both time and spatial information. The value of the data is directly related to the business value. In many circumstances, IoT applications process data from several places in a timely manner. Cloud computing now makes it possible to process data from several locations in real-time.

D. *Privacy and Security*

Upon the onset of IoT technology, smart devices are going to collect and send information about the consumers to a number of different entities without their knowledge. These are one of the actual issues that need to be tackled with the help of appropriate security and privacy policy framework.

1) *IoT Big Data security*

Data from various IoT sensors is frequently related with cybersecurity concerns and privacy concerns. In the case of IoT analytics that entail the processing of personal data, cybersecurity is required to protect the information. As a result, contemporary cybersecurity solutions are required to support IoT analytics.

2) *Cyber security*

Privacy has been one of the most significant issues of IoT analtyics. The private information of the user must be secured and shielded from outside influences. Though the current security algorithms provide primary encryptions to secure data, still more dynamic algorithms are required to enforce privacy of streaming data.

3) *Trust Management*

To obtain adequate confidence from the IoT users, appropriate trust management must be constructed to effectively perform counter attacks. A trusted processing entity is needed to control data access based on privacy policies, because data privacy protection is one of the significant features for realizing data trust in IoT.

4. Prescriptive Analytics Platforms, Applications, approaches and models in IoT

A. *Prescriptive Analytics Platforms in IoT*

Several existing platforms are said to be capable of delivering real-time analytics. However, as a result of various performance trade-offs, these systems appear to be insufficient for large amounts of IoT data in their current implementations. For example, it was discovered that distributed in-built memory and other resources were a major pre-requisite for doing IoT analytics, which resulted in considerably long latencies. As a result, it is clear that building IoT analytics solely from the standpoints of software and hardware is insufficient. To put it another way, the distributed hardware resources must be interconnected by a reliable network so that software platforms can fully utilize the available resources to provide real-time IoT analytics [1]. Table III summarizes the different platforms in IoT and their features. All the platforms listed in the table such as Apache Spark, Apache Flink, Apache Storm, Druid, AWS etc are the open source paltforms that facilitates the real-time processing of IoT data streams, with their unique significance.

B. *Prescriptive Analytics Applications in IoT*

Prescriptive analytics has limited application on IoT domain while it is still in its incubation. Table IV covers the different use cases of precriptive analytics on IoT data streams. Smart store applications use optimization model to track the surveillance of items in the shop floor. Vehicle routing, prescriptive maintenance of defective automobiles, smart metering are the other applications that uses prescriptive models in order to study data that are evolving over time.

C. *Prescriptive Analytics Approaches in IoT*

Prescriptive analytics is a process that analyze data and provide recommendations by optimising decisions ahead of time. Till date the prescriptive models built are domain specific as there is lack for dynamic models that can adapt for diffent domain.

1) *Reinforcement Learning*

Reinforcement Learning (RL) is identified as the effective strategy for procative decision making [37]. RL solves issues with sequential decision-making by utilising the concepts of agent, environment, states, actions and reward by Markov Decision Process [38]. Successive observations are made before a final decision is made. In RL, usually problem is represented by an environment comprising of state, action and learning agents with a defined goal state. The agents are said to reach the goal by experiencing and discovering optimal sequence of actions [39].

2) *Interactive Reinforcement Learning*

It is the human centered reinforcement learning, where humans interact with the agents and teach how to achieve goals. Humans change the optimal behaviour of agents by giving them inputs as convenient to them and overcome the pre-programmed behaviour [40]. Human trainer observes the agents performing task and provide the instant feedback based on human evaluation of actions. The agents continually ineract with humans until an optimized action is achieved [41].

3) *Multi Objective Reinforcement Learning*

In every sequential decision making strategy, there is a significant cost/reward involved in achieving each objective. MORL is a strategy that combines multi-objective optimization and RL approaches to address sequential decision-making issues with multiple objectives [42]. Pareto dominance and scalization are the two techniques for solving multiple objective optimization problems.

D. *Prescriptive Analytical Models in IoT*

1) *Probabilistic models*

Probabilistic models assess the dynamics in data to predict the events that are likely to occur in the future. This involves the models that represents the cause and effects relationships [43]. The most significant techniques under this include Markov Decision Process, hidden Markov model and Markov chains.

2) *Machine Learning/Data Mining*

Artificial intelligence includes machine learning as a subset, whose algorithms rely on models for data processing. In order to perform judgments or predictions, machine learning algorithms build models from sample data, also referred to as ”training data.” [43]. Machine learning and data mining are treated as one category as they are closely ineterrelated. Together, they build the models to predict the future outcome and instantly the best course of action.

3) *Mathematical Programming*

Mathematical Programming refers to the optimal allocation of resources among competing activities. It aims at providing best course of action for complex decision making problems.

4) *Evolutionary Computation*

Evolutionary Computation is a collection of algorithms that rely on trial and error to solve problems. A first collection of independent solutions is developed and updated progressively. Every new generation is created by deleting least desirable solutions and applying modest random variations in a stochastic manner. Evolutionary computation is used in prescriptive analytics to solve difficult problems in data-rich situations where no precise solutions exist. [43].

5) *Simulation*

Simulation is the strategy of imitating a hypothetical or real-world scenario using a computer to investigate how the system functions [43]. Prescriptive analytics employs it to enhance earlier decisions made. It promotes the best decision by changing the variables and evaluating the new ideas that can be incorporated.

6) *Logic based models*

The sequence of events that results in the desired outcome is hypothetically represented by logic-based models. They may use rule-based systems, expert knowledge representation, and domain knowledge elicitation in the context of information systems to aid dynamic judgement in the applications of prescriptive analytics [43].

TABLE III. Platforms for IoT data analytics in real-time

Software Platform	Unique Features	Advantages
Apache Spark [28]	Processing in real time, quick processing, ability to connect to Hadoop and current Hadoop data	In- memory processing, distributed processing, ideal for analytics in real time, resilient to faults
Apache Flink [29]	Open source software, pipeline architecture, real-time analytics, large-scale data processing unit	Iteration processing is faster, memory management is better, latency is lower, and garbage collection is more efficient than Spark.
Apache Storm [30]	stream processing in real time, a distributed, open-source system, resource aware scheduling	Extremely low latency, huge scalability, fault tolerance, and real-time distribution computation are all features of this system.
Druid [31]	Open source analytics platform, large-scale data input in a flash, and real-time analytical processing queries	Fast ingestion and low latency queries, as well as fault tolerance, make it ideal for real-time IoT analytics.
AWS [32], [33]	Secure cloud platform offers wide cloud storage for application development.	AWS supports on demand infrastructure to accommodate need of IoT system. AWS is more flexible with IoT applications in usage of tools and resources
Azure [33]	It provides with an open source platform to build a robust application	Enable highly secure and reliable communication between IoT applications
SAP [34]	Integrate IoT data into its analytics solution to improve data analysis and visualisation	Highly effective cloud analytics with live connections provide quick data retrieve and a better user experience

TABLE IV. Use cases of prescriptive analytivs on IoT data streams

Application domain	Data set	Models
Smart store [12]	RFID data set	Optimization model
Vehicle routing [35]	-	Decision models
Prescriptive maintenance [16]	Airbus A320	Discrete Event Simulation
Learning of Time-dependant parameters [3]	UCR Time-series archive	Change detection model
Smart metering [36]	Open load data sets	Clustering-based heuristics

5. Conclusion and Future enhancements

This paper is a review of several papers on IoT data analytics and prescriptive analytics. Prescriptive analytics is the new trend of business analytics that is still in incubation. This paper attempts to investigate the possibilities of prescriptive analytics with IoT data streams. It describes the various issues and challenges that IoT analytics is now dealing with. There is discussion of several tools and platforms for IoT data analytics. In addition, an outline of prescriptive analytical models was provided.

Prescriptive analytics is an imminent and critical advancement in the field of IoT data analytics that is essential to improve decision making and processes effectiveness. According to the study, prescriptive analytics on IoT data streams is still not widely used, and so there are very few articles in the literature. Future research will focus on developing automated optimised prescriptive models for a variety of IoT applications that generate dynamic data streams.

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