Survey on IoT Data Analytics with Semantic Approaches

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ABSTRACT

Data generated from the Internet of Things (IoT) devices that are mostly cheap enough for any specific use case. It shows the ability to gather data about the physical environment and to understand real-time context, combining with other heterogeneous data sources such as sensor networks, social media, crowdsource data collections, etc. Data analytics can enable a massive set of new services for IoT applications. The management of data in an ultra-scale network which is continuously expanding leads to concerns in data analytics and management. The researchers have examined the challenge of interoperability of applications and services among IoT applications to address them. The common problems of interoperability come from different levels, from syntactic to semantic. In this paper, we take a broad view of current IoT analytics work where Semantic Web approaches aim to solve the semantic interoperability by exploring recent studies in IoT systems. The paper taxonomized literature based on the interoperability requirement of the IoT system. This study identifies the opportunity resulting from the convergence of the Semantic Web and IoT data analytics.

CCS CONCEPTS

• **World Wide Web**;

KEYWORDS

Internet of things, Sensor network, Semantic Web, Semantic Data Analytics, Web of Things, Semantic Middleware

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1 INTRODUCTION

IoT with interconnected devices comes along with the explosion of data that takes humans to the decade of diverse data and smart things. IoT does not only connect devices but also has the potential to interact, share, and provide useful insights with its data analytic capability. It is estimated that in 2025, there are nearly 80 billion connected devices over the world[1] that generate quintillions of bytes every day. This amount of data is not possible to store in a traditional way, and consequently cannot be analyzed afterwards.

Analytics, when applied to data, can derive knowledge and insights from data [10]. Combined with many disciplines, it could overcome the limitations of abstract process models and come alive with the data. In the context of the IoT, data analytics and process analytics can be defined as steps in which a variety of IoT data reveals trends, unseen patterns and deduces information. IoT data analytics can extract knowledge by the integration with other smart technologies such as Semantic Web. IoT data analytics is a vast, broad vision and spreads up from infrastructures to applications. The current challenges in IoT applications are the interoperability in a technical and even more semantic sense. Technical and physical connections are surveyed and well supported, both academia and industry are working to resolve the interoperability in services and information of IoT applications.

Although some aspects of the Semantic Web technologies for the IoT have been investigated already, a systematic review that follows the structure of Semantic IoT solutions is yet to be conducted. Payam Barnaghi et al. [21] surveyed a vision of Semantics for the Internet of Things by looking back to the Semantic Web communities' developments, highlighting the advantages of semantics and showing the challenges of applying semantic technologies to the IoT. IoT devices and sensors are the potentials of data collection in the scope of both innovative urban life and industries. Our study is surveying the works on the using Semantic Web technologies to IoT for the data analytics. This study aims to investigate the interoperability of applications and services, especially semantic interoperability in the IoT data service domain. The first motivation of this study comes from the main characteristics of the IoT global scale, interconnectedness, and the potential for societal impact through advanced IoT data services. Secondly, based on the semantic interoperability principle, we would like to identify the current efforts to solve interoperability challenges in IoT data analytics. On the other hand, almost all surveys in IoT are more focused on physical interconnection protocol topics than considering the traction of IoT data and IoT big data analytics. Meanwhile, IoT data has become a huge potential source for analytics.

Given the potential of IoT data analytics and foreseeing the research trends to understand the insights from IoT data, we focus on taking an in-depth overview of IoT data analytics with semantic web approaches. This contribution of the paper is then to:

[1]https://www.statista.com/statistics/471264/iot-number-of-connected-devices-worldwide/

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- Review research works on IoT analytics and applications with semantic approaches.
- Review semantic interoperability in the IoT domain.
- Identify gaps and needs towards seamless application development.

2 METHODOLOGY

IoT data analytics has emerged by plenty of work, and Semantic Web technologies also address data integration and processing. To categorize the semantic aspect in IoT data analytics, we provide a comprehensive survey by a systematic review of the existing work on data analytic with structured Semantic approach in the IoT system and study the semantic interoperability in IoT applications and services.

To achieve these goals, we employed an approach of identifying the methodologies and frameworks of Semantic data analytics in the IoT networks. We do the search across a structured literature research to identify the related works since 2010s with our pre-set keywords. We organize these works manually following by (1) Semantic IoT data analytics, (2) IoT streaming data analytics, and (3) Semantic IoT service computing. We search for the research and funded projects in semantic analytics for the IoT using relevant keywords: "semantic service-oriented middleware," "semantic IoT analytics," "Ontologies-based Internet of Things middleware," "Semantic Interoperability," "Semantic Web of Things." Subsequently, we take an in-depth review of the current state-of-the-art of applying the Semantic Web technologies in IoT data analytics. Our goal is to consider the current works to solve IoT interoperability by a wide range of Semantic Web technologies, from infrastructure, storage technologies to queries and reasoning.

We guided this survey by evaluating Semantic Web technologies that impact the data analytics process, from data to system and security issues. This paper addresses the literature review of semantic IoT data analytics by the following topics: Streaming data processing (+queries), Semantic/ontological service computing, and process analytics for IoT application domains.

Section 3 surveyed the semantic data and process analytics in various disciplines with Semantic Web approaches. This section considered studying the semantic interoperability in IoT applications and services by reviewing the current Semantic Web technologies for developer IoT applications and services and survey the aspect of SW technologies for IoT data analytics. We take a deeper investigation of the application and development of IoT systems with SW such as CEP, Ontology-based, Machine Learning, and Service-Oriented Computing. We then discussed current limitations and address the research challenges in the Section 4. This paper is concluded with Section 5.

3 LITERATURE REVIEW ON SEMANTIC IOT DATA ANALYTICS

"In the race of designing IoT as part of the Future Internet architecture, academia and Information and Communication Technology (ICT) industry communities have realized that a common IoT problem to be tackled is the interoperability of the information and services." [24] This report stated four levels of interoperability in IoT networks and there are (1) technical, (2) syntactic, (3) semantic,

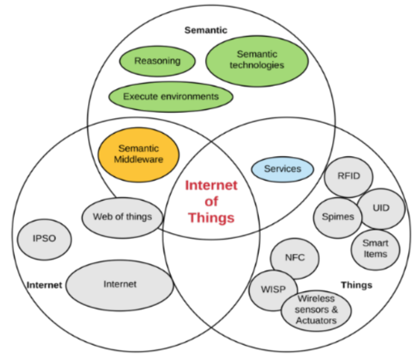

Figure 1: IoT paradigm of the convergence of different visions – "The Internet of Things: a Survey" [3]

and (4) organizational [32]. By providing the semantic description and based on background knowledge, Semantic Web can increase the semantic interoperability in IoT services and information. In the form of Services and Middleware environments, several Semantic Web can perform well at dealing with the semantic level of the interoperability, as in Figure 1.

In this section, a literature review on a set of Semantic technologies into IoT applications and analytics is investigated and that covers the main survey goals. The study contains the following categories: IoT Streaming data processing; Semantic/ontological service computing for IoT; Process analytics for IoT application domains.

3.1 IoT Streaming data processing

The Web of Things (WoT) has been included with well-defined standards and description frameworks (RDF, OWL) for the data annotation and knowledge representation. SPARQL recognized as one of the crucial technologies of the Semantic Web by official W3C Recommendation[2] . The heterogeneous devices and the connection of IoT networks have been increasing the stream processing demand over the data and network. When it is translated to Semantic Web, SPARQL plays an essential role in processing agents' data, and it has implementations as rules and updates events in the event processing network. "Reasoning" becomes a popular term within Semantic Web technologies when it tries to make conclusions and return new facts to the knowledge base. From the beginning, the reasoning base on first-order predicate logic and description logic such as SWRL,[3] RIF[4] that derived the new term from a predefined rule. Therefore, the reasoning engine has been built by handling the set of RDFS and OWL vocabularies such as in the Jena Inference subsystem.[5] IoT networks need to handle data in real-time or semi real-time; eventually, reasoning, and complex event processing are the high prioritized when dealing with IoT networks. To work with stream processing, SPARQL must be extended for querying over continuous distributed data streams. A number of works on the

[2] "XML and Semantic Web W3C Standards Timeline" (PDF). 4 February 2012.
[3] https://www.w3.org/Submission/SWRL/
[4] https://www.w3.org/TR/rif-overview/
[5] https://jena.apache.org/documentation/inference

Table 1: SPARQL streaming process

SPARQL Stream processing	Approaches
C-SPARQL	Compute aggregate values over the windows
CQELS, SPARQLStream, MorpgStream	Timestamp() function
EP-SPARQL	Detection
SPASEQ	Semantic Complex Event Processing operator
CACEP	Fuzzy ontology
INSTANS	SPARQL Update user configurable

SPARQL extensions have been deployed to retransmitting, processing RDF and Linked Data streams. [27] showed promising results in data management and event processing challenging topics for raising the WoT. The RDF Stream Processing (RSP)[6] communities implement these research activities and grow to produce datasets, benchmarks and systems to compare with other criteria.

On the other hand, to meet the real-life requirements of stream processing, the current RSP methodology must be extended. C-SPARQL [4] is an early proposal for the extension of SPARQL that distinguishes feature support for continuous queries over RDF data streams; this is the first work to demonstrate windows-based stream processing. [7] extending the logical SPARQL algebra for stream processing on the foundation of temporal relational algebra based on multi-set; this study transforms SPARQL queries to a new extended algebra and defines executable physical counterparts. EP-SPARQL [2] is a unified language to bridge the gap with background knowledge - describing the context or domain in which streaming data are interpreted - in analyzing the event stream by combining semantic and event streams. EP-SPARQL provides syntax and formal semantics of the language and an open-source prototype implementation. This work was focusing on the detection of RDF triples in the specific temporal order. Working with the timestamp function, [23] presented a platform-agnostic execution framework towards RSP, so-called Continuous Query Evaluation over Linked Streams (CQELS). This framework is planned to work on embedded devices and cloud infrastructure also. To take full advantage of SPARQL 1.1 update,[7] INSTANS [25] enabled user-configurable the entailment rule in streaming processing framework with SPARQL Update (INSERT, DELETE) One of the latest work on the semantic Complex Event Processing is implemented by [15], namely SPASEQ that extends SPARQL with new Semantic Complex Event Processing operator s that can deal with RDF events. [31] proposed a Context-Aware Complex Event Processing method (CACEP) that uses fuzzy ontology to represent the context. CACEP still faces the performance and scalability of the ontology due to the complex event.

The characteristic of IoT is that data comes from heterogeneous source; distributing reasoning tasks can improve the analytics process with large data sets and heterogeneous data sources and hence improve the performance of the knowledge system. Marvin [22] was a parallel and distributed platform that processes RDF data on a network of loosely coupled peers. OWL2EL[8] provides the ability to model large ontologies and IoT streaming data as well as an efficient reasoning service. [13] describes a distributed reasoning system reasoner for OWL2EL applying to traffic data. It described an open source framework where ontologies are generated from streaming data by the reasoner process. Perform on the large-scale knowledge graph, SANSA framework[9] uses a semantic analytics stack providing functionality for distributed computing. It leverages data integration and modeling provided by the Semantic Web and Machine Learning [30].

3.2 Ontological service computing for IoT

The Service-Oriented Computing (SOC) infrastructure addresses clearly its vision, "describe the various aspects of a (Web) Service using explicit, machine-understandable semantics, that can enable automatic discovery or composition of complex (Web) Services or facilitate seamless interoperation between different (Web) Services" [29]. The Ontology services in a SOC can present the concepts and the relationships of data/services. Not just considered as a data model, but ontologies also describe the relation of concepts and provide the knowledge base for analysis and reasoning over data. Developing Ontology-based event models is the motivation that leads to high-level interpretation. Researchers are studying the application of semantic computing in the IoT context in the current Semantic Web landscape. WoT semantic interoperability is the main key challenge to step up the next generation of the Web. Various ontology-based software tools/services for IoT and WoT have been deployed to validate and modeling the data. Several projects use Semantic Gateway as a Service for large multi-institutional projects such as CityPulse [5]. Besides the software tools that aim to improve semantic interoperability, the Ontology-based catalogs relevant for IoT that encourage the reuse of ontologies, in the Smart-city domain. Projects such as OpenIoT [33] applied ontologies-based information integration to increase the semantic interoperability between IoT applications and physical/virtual devices. [18] proposed a model-driven methodology (Ontology Library Generator) to update existing ontology development libraries and frameworks. This software suite hides all the complexity of ontology-based development for IoT developers. [35] was a framework building an information modeling environment provided by sensors and regulatory information. The framework showed efforts in the use of Semantic Web technologies in order to build an environmental monitoring system, but the interoperability challenges still remain. The global scale of the IoT came with security vulnerabilities since it is based on the Internet protocol and can communicate without human intervention. The emergency of IoT nodes had led from the wide range of

[6]http://www.w3.org/community/rsp
[7]http://www.w3.org/TR/sparql11-update/
[8]https://www.w3.org/TR/owl2-profiles
[9]http://sansa-stack.net/

the IoT application from healthcare to intelligent transport with the increased number of IoT devices and networks. Focusing on the improvement of IoT cybersecurity with ontologies-based solutions, [17] proposed an ontology-based cybersecurity framework using knowledge reasoning, composed of two approaches: design time and runtime. This framework helped to monitor the business process and gathered cybersecurity alerts and possible threats from the contextual information of security. Another effort in the security service framework for IoT-based; [28] highlighted a multi-layer cloud architectural model that uses Ontology to better solve the heterogeneity issues in the presented layered cloud platform and ontology-based security that supports security and privacy preservations. The remaining challenges of interoperability and security have been discussed in the IoT of future domain applications such as smart home, smart cities, then open a direction for future works on IoT security and privacy.

3.3 Process analytics for IoT application domains

The business process analysis persists challenges as it is equipped with IoT and sensor devices such as dynamic processes, highly complex, or maybe multi-domain processes. Being increasingly electronic tracked will create a massive amount of data; the data can provide new insights with process analytics in IoT. Jasmien et al. [19] brought up the business process on the semantic Web and defined an agent's ontology. This work has been fulfilling the essential functions of the agent system and addresses the heterogeneous knowledge with rule-based reasoning on the business process.[6] modelled business processes that are able to be performed by Web Services by using a semantic matching algorithm to perform required business processes. Dealing with the crucial issues in the Digital Ecosystems of service information, Hai Dong [11] presented a conceptual framework that focused on discovering, annotating, and classifying the service information with the Semantic Web technologies. The study combines the specialty of ontology-based metadata classification and metadata abstraction. [9] introduced a Semantic Web-based solution that provides context ontological reasoning service for multimedia conferencing process management. Utilizing to create multimedia conferencing ontologies, they designed corresponding business rules; thereby, the ontological reasoning efficiency was enhanced. Juan Du [12] proposed a flexible distributed information integration mechanism by developing ontology-based management support to facilitate creating a prefabricated cloud component supply chain. This work aims to solve the complex management decision in the prefabricated components supply chain.

There are plenty of works that implement the benefits of Semantic Web and IoT for application domains such as environment protection, health care [16], agriculture [18], smart supply, that usually use ontology-based approaches. However, the IoT applications did not explore or use Semantic Web characteristics, i.e., reasoning, sharing, and reusing knowledge, due to current limitations such as performance and ontology standards. In the next section, we will discuss an effective way to implement Semantic Web technologies for IoT applications and data analytics.

4 FINDINGS

The interoperability of the communication and service in IoT is the critical challenge that, if solved, will unlock the potential of the IoT. The IoT data, when applied to the applications, faces many limitations due to non-standardized formats. Semantic Web Storage Technologies can perform well on an ultra-scale IoT network. Linked Data can combine aggregation work to access Linked IoT data from distributed sources and lead to the future federated querying on the IoT network. However, IoT Linked-Data needs to improve the potential semantic due to their linked characteristics in combination with Data mining. The number of SPARQL endpoints has increased on the Web in the last decade and becomes the primary preference to access data on the Web because of the flexible way to react with the Semantic Web of Things. SPARQL has the potential to deal with the global schema of Web data by its characteristics. Considering the amount of work of SPARQL and its characteristic of SPARQL as rules to explore the dataset, SPARQL is a powerful tool on the Web of Things that has the potential to perform the reasoning for IoT data analytics.

The Semantic Web framework can support machine learning in every individual layer due to the data structure, ontology-oriented knowledge representation, and linked data principles. A number of studies have implemented knowledge engineering and AI techniques to IoT networks for representation, integrations, and reasoning in the past decade [14] [26]. [1] presented a characterization of the Data Warehousing/OLAP environment by introducing the relevant Semantic Web foundation concepts. This survey also reports the use of Semantic Web technologies for data modeling and data provisioning, data annotation, and semantic awareness. The ontologies solution for IoT has been getting attention in the early state; most existing ontologies focused on modeling the IoT devices. There are two conventional methods to describe IoT devices with ontology: the physical properties and the human perception of the entity. In service-oriented middleware, ontologies can be a backbone of the knowledge base. To provide semantic interoperability, further works need further steps by modeling the context information not only in IoT but also in the Web.

The requirements of simplifying the development of new applications and services in IoT help developers focus on developing IoT applications. The IoT middleware encouraged by a software layer between infrastructure and applications aims to support the requirements of IoT applications. [8] listed the challenges in middleware solutions for the IoT that show technical challenges and open issues in middleware: Standardization; User Interface Provision; Storage Capacity and Security, Privacy. [20] addressed the dynamic semantic interoperability of control in IoT-based systems and convince the need for adaptive middleware for IoT systems. Most of the data of sensor networks or the Internet of things comes in real-time or nearly real-time, and although IoT applications have to deal with IoT data before, the possibility of describing and deduce knowledge of time-series data is still an open challenge for IoT applications. IoT middleware service is a promising potential to solve the semantic interoperability of IoT interoperability.

Much of the work to improve semantic interoperability has been carried out and reviewed in this section; however, some limits need

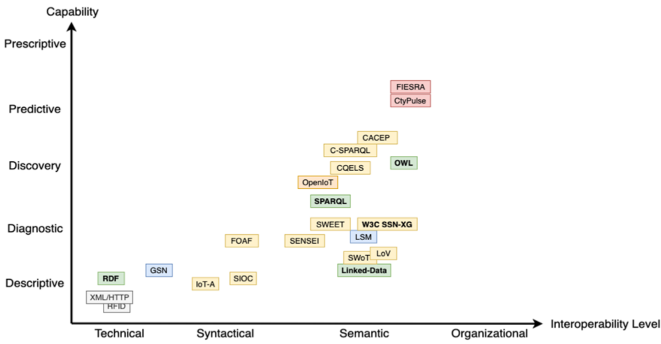

Figure 2: The interoperability level of recent SW's efforts

to be overcome. Semantic Web technologies play an essential role in solving the semantic interoperability of information and services.

5 CONCLUSIONS

Network interoperability challenges are well supported by the most recent middleware approaches that we highlighted in the previous section. However, semantic interoperability is still a big challenge in IoT network analytics. Nevertheless, the Semantic Web is not a magic tool that solves interoperability in the IoT. Semantic Web is good in a specific domain and must be combined with other technologies to solve interoperability. On the other hand, the lack of standard and semantic interoperability in IoT built a barrel for IoT application development. In particular, enabling semantic interoperability remains the persistent research challenges:

The complicity of distribution & the hierarchy of interoperability

Within the IoT network, where data is increasing continuously and distributed in dynamic mechanisms, semantic interoperability is essential to provide service interpretation. The requirement of a flexible way of interoperability is the key challenge of defining an IoT system's ability to exchange information and knowledge. More recent evidence highlights that the multi-level interoperability is performing well by new technologies such as RFID, COAP, XML. However, those technologies still face challenges in terms of content and context exchange in the concept of semantic interoperability.

The performance of the global-scale and the velocity of the data

The hyperconnected world of advanced technology from different fields realizes an automated global network of devices that regularly communicate. Despite the adoption of computing and storage technologies, the global scale, and the velocity of IoT data are significant challenges of current IoT system development.

The requirements of security at the semantic level in the context of the heterogeneous device's interoperability

To ensure the transition between devices beyond heterogeneous IoT sources and delegate security decisions among the IoT system, the interoperability must resolve the security issues at the semantic level. Those issues can improve security at the semantic level by defining the context of security.

To resolve the main challenges of semantic interoperability, the main focal research challenge is addressing as follows: A real-time data analytic and replay events log on existing IoT data/process models to identify various scenarios and an abstraction of them in mathematical models. A solution to meet the challenges is to create a flexible framework, enabling the user of every IoT platform to select and modify tools to interact with IoT streaming data. The Service-Oriented Middleware (SOM) provides interoperability of applications and services and is designed for various applications and covers multiple domains, languages, and infrastructure. Semantic SOM can help to improve the performance of the IoT scale due to the global scale and heterogeneity of connected devices. With the characteristic of reasoning, global query, and background semantic, the Semantic SOM is a flexible way to improve the semantic interoperability of information and services in IoT.

IoT analytics is an essential participant in any IoT application over any domain. The review on IoT data analytics in this paper provides a taxonomy that addresses Semantic Web technologies' contribution showing the current limitation and looking for research challenges. We are looking forward designing a semantic service-oriented middleware framework processing the raw IoT data dealing with high-scale data and massive datasets. This framework could provide semantic facilities for presenting, querying, reasoning, security, and data analytics.

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