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In-network Distributed Analytics on Data-centric IoT Network for BI-service Applications

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ABSTRACT

In-network distributed analytics are the major research challenges on data-centric IoT network. The rapid growing IoT applications on BI-services desire a generic framework in order to handle the dynamic analytic work load and disparate IoT data sources, because the generic framework can only perform the actions based on knowledge extracted from IoT data sources. So for knowledge analytics, there is always a need of novel framework and to achieve this, is a research task. The real time IoT driven applications always desire in-network analytics in order to transform the big business data into instant revenue of goldmines. The paper aims to discuss a knowledge analytic framework at IoT structure level and an IoT operational platform, so as to cop up with in-network IoT based BI-service applications. Here assume that each structure having a set of IoT nodes with one or more analytic nodes depending on application area of interest and the neediness of the deploying environment. Discussion shows the sound feasibility of Visual knowledge production frame in terms of knowledge abstraction, energy minimizations, and BI- service safety intensification.

Keywords: Data-Centric IoT network, BI-service, IoT Application, In-Network Analytics

I. INTRODUCTION

In the current and upcoming days, the knowledge analytic tasks are gaining popularities across various Intellectual BI-service applications. The main aim is to acquire the insights from large scale IoT network that can be used to produce intelligence for the BI-applications. In the current Intellectual BI-service applications, the network-centric data are highly unstructured and ambiguous, and create research challenges in inferencing the potential knowledge. The time to insight is very slow, quality of insight is poor, and cost of insight is high, on the other hand, the Intellectual BI-service applications requires low cost, high quality, and real time frameworks and algorithms to massively transform their data into cognitive values of goldmines. Such cognitive values are utilized as knowledge and insights for creating worth of the Intellectual BI-service applications.

With the advancement of BI-service revolutions and IoT evolutions, large numbers of applications are researched for the real time data-centric IoT network to automate the BI- service process that anticipates with high degree of Business risk [**1**].

The real time data-centric IoT network mainly insists the in-network activities through the minimal support of IoT's data accumulations capability, data processing capability and data storing capability. In large real time application where the IoT nodes and analytic nodes are housed together, the analytic node cannot take any instant intelligent actions from the largely accumulated raw IoT data, so at right time proper knowledge need to be discovered by analytic nodes to perform critical risk driven actions for BI-service. The improper knowledge collections may lead to damage of BI-service reputations and financial loses. We consider a data-centric IoT network to BI-service application in order to keep track and manage various unforeseen business situations.

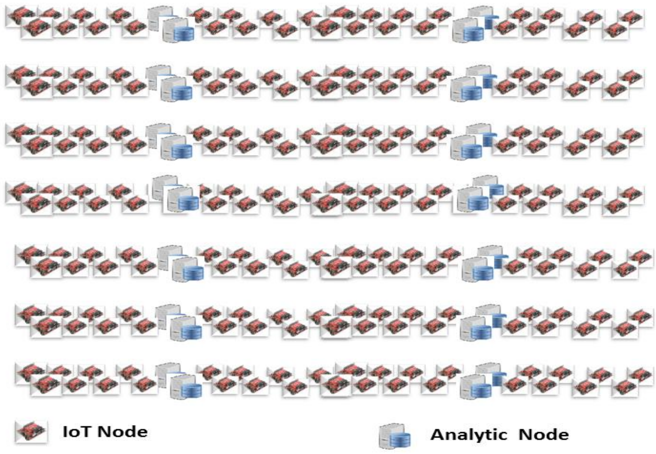

Figure 1 : Line structures of analytic nodes and IoT nodes

The Fig-1 describes the organization of line structures that consist of the mixtures of IoT nodes and analytic nodes; however the organization of line structures depends on application area of interest and the neediness of the deploying surroundings. The data centric IoT network can be locally partitioned into several line structures and in in each line structure, the IoT nodes and analytic nodes are placed and configured so as to minimize the congestion of network traffic.

II. RELATED WORKS

The data-centric IoT network is broadly entitled as the data producing hub where large and bulk amount of raw data are produced. Much literature has focused numerous ambient issues of data collection approaches for data-centric IoT network where in-network data processing and management activity are fully emphasized [**2**].

In data-centric IoT network, the flat structure may not be efficient enough for active data collection; however the structure based data collection approaches have gained better performance. The quality, reliability and accuracy are the most important parameters which are to be considered during IoT's data collection to achieve the total quality management. The energy efficient data collection strategies are emphasized to increase the overall network life [**3**]. The data-centric IoT network has also major contributions for safety critical applications to accumulate the real time data with strict timelines and threshold. The real time IoT data can be made applicable through knowledge data discovery process in which data mining, data warehousing and computational intelligence are blended to the common goal of data-centric IoT network application [**4**].

For the sake of unify knowledge collection framework, the study has been made from data collection to knowledge discovery with a broad aim to migrate the knowledge from disparate IoT data sources.

In context to the knowledge analytics and re-analytics for customer end and enterprise end business intelligence domain applications, the functions of several analytic operations and BI applications are analyzed to design various intellectual BI frameworks [**5, 6**]. The BI manufacturing service system uses IoT and cloud computing technology for storage, analytics, and other analytic operations. We also analyze an e-commerce service application for BI process monitoring system. In order to implement the analytics in deception detection service, the implementation of machine learning system as a mechanism to execute the analytic operations for the said business intelligence service. A number of innovative analytic operational analyses are considered for diversified BI service applications, such as, product life cycle management service, transport logistic service, and supply chain management service. Almost all BI services use a cognitive based smart logistic framework in order to transform the big business data into instant revenue of goldmines [**7, 8**].

The broad review on those BI service applications gives a vision to numerous analytic operations that can be implemented on In-network distributed Analytic platform on Data-centric IoT Network for BI-service Applications.

III. ISSUE ANTICIPATION

Three activities are mainly to be synchronized within strict timelines for any real time data-centric IoT network application: data collection from IoT, knowledge transformations and knowledge dissemination by analytic nodes and it is essential to bind all three activities into a common framework [**9, 10**]. The real time data-centric IoT network is configured to monitor business critical applications whose failure leads to damage of BI-service reputations and financial loses. The application usage is purely in-

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network BI- service applications for BI-service monitoring and control. The analytic node is an autonomous microcontroller that acts as dedicated cluster head to which require number of IoT nodes are connected within multi-hop network. The analytic node senses the data from IoT environment and performs further processing. Energy should not be made any constraint for in-network business critical applications: IoT and analytic nodes can able to store energy from electricity; still we are trying to minimize the overall energy consumption. Analytic node cannot work intelligently with the raw sensed IoT data, thus an appropriate framework is needed to yield filtered knowledge. The analytic node must capable to determine the emergency to generate quick awareness about the emergent situations.

The analytic node receives the large continuous mess data from IoT nodes, process those data using a knowledge discovery framework to produce the desired knowledge. The analytic node then transfers the knowledge to a knowledge warehouse server from which knowledge users can access for further actions.

Structure level knowledge pool

Our proposed structure level data-to-knowledge migration framework ensures to send the optimal knowledge from IoT nodes to the analytic node within the strict timelines. In order to make necessary processing at structure level only fraction of second may be required to meet the real time system needs.

As described in fig-2 five logical processes or functions are to be performed by the analytic node's processing unit to obtain the visual knowledge from IoT data and ensure a complete knowledge data discovery (KDD) process before being transmitted the visual knowledge to knowledge warehouse that can be accessed by knowledge users. Data selection extracts row data from IoT data sources and passes the row data for data preprocessing in order to obtain the cleaned data. The cleaned data are fetched to data alteration process in order to obtain the data in desired data format.

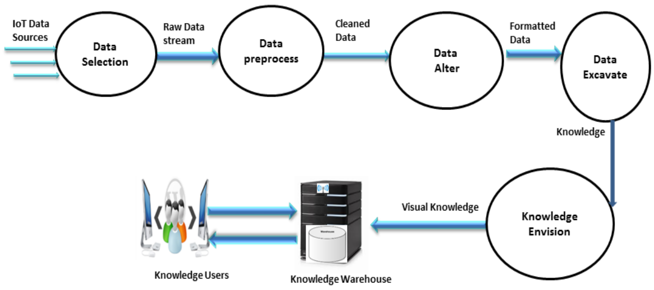

Figure 2: Visual knowledge production from IoT data sources

Data excavate only receives the useful formatted data based on valid range in order to produce the knowledge and insights which are further passed through knowledge envision to produce visual knowledge. The visual knowledge is stored in knowledge warehouse from which the knowledge users infer intelligence that can be well perceived by the BI-service to track and perform cognitive actions.

The knowledge production frame is purely an energy saver framework to minimize the knowledge production work load with drastically reduce the energy consumptions of analytic nodes.

IV. IMPLEMENTATIONS FACTS

Consider a data-centric IoT network environment, in which all static IoT nodes and analytic nodes are wirelessly connected through any evolutionary IoT network within multi-hop distance such that each analytic node acts as permanent dedicated leader to the partially distributed network. All IoT nodes are battery powered, but can harvest energy from electricity. Each analytic node is an autonomous microcontroller that equipped with powerful processing, communicating and storing units to carry on consistent data processing operations. Here the IoT nodes have the communication range to analytic node and the analytic nodes have the communications range to knowledge warehouse servers to disseminate the knowledge.
It constitutes a distributed knowledge analytic IoT Platform to implement the Visual knowledge production frame from IoT data sources.

Here dedicated structure head acts local analytic node. The data flows only from IoT nodes to analytic node. In analytic node, data is migrated to visual knowledge (actionable data) and passed the knowledge to the knowledge warehouse server via base station and gateway, where the knowledge users make further analysis to take necessary actions and precautions.

This operational platform has real time implementations in safety critical BI-service applications in order to track the unanticipated events inside the business. In risk driven BI- service applications one-hop topology may be preferred to use due to non-stop delivery of confidential data from IoT end to analytic node end without any interference. But for BI-service feasibility case, we consider a multi-hope IoT network for in-network knowledge analytics.

Base on protocol, the knowledge users send their request to analytic node through knowledge warehouse server to extract specific information's relate to safety, security and the internal status of the BI- service environment.

V. DISCUSSIONS

We describe an operational platform for in-network safety critical BI-service application to detect and resolve the prospective extortions of the data driven business industry. We implement IEEE 1451.5-802.11 standard for data-centric IoT network to construct the multi-hop structured line grid network, in which, analytic node is an autonomous microcontroller device and contains an 802.11 wireless radio to wirelessly communicate with the local analytic node.

We also discuss a Visual knowledge production frame (fig-2) that runs at individual analytic node to filter useful visual knowledge that are disseminated to knowledge users to perform timeliness intelligent actions so as to protect the BI driven service industries from highly unexpected misshapenness. So our approach upholds the BI-service safety intensification by resolving prospective extortions. The figure-3 describes the knowledge Visualization context in a two dimensional grid structure. In figure-4, the study reveals that the volume of IoT' raw data is much higher as compared to volume of actual filtered knowledge. Out of N bytes raw data only 2.66% packed visual knowledge can be yield, but transmitting such voluminous raw IoT data would lead to huge traffic congestions and energy consumptions. So it ensures to preserve 97% of transmission energy and also 3% packed visual knowledge can be well perceived to perform BI critical actions so as to resolve the extortions of the BI-service industries.

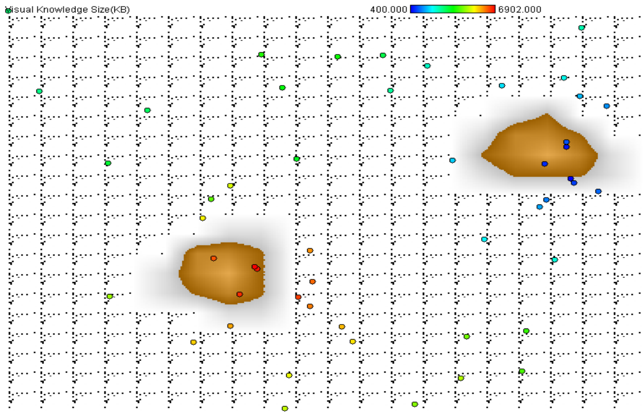

Figure 3: knowledge Visualization context in a two dimensional grid structure

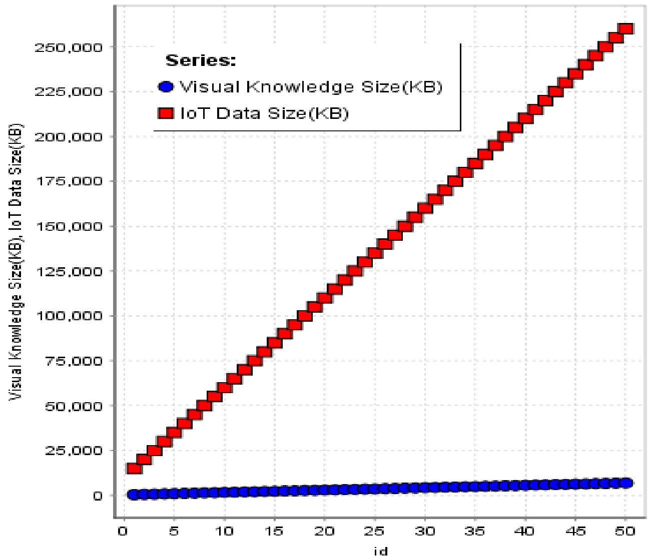

Figure 4: IoT data Vs. Knowledge size in a two dimensional grid

The IoT has a most important influence on the Big Data background. The key awareness on IoT data analytic evolution is that every IoT object has an IP address and connects to each other. Now, bearing in mind the circumstances of trillions of such connections that may be producing massive volumes of data (IoT big data), and the competence of current knowledge analytics mechanisms are going to be challenged. The IoT evolutionary network connects people, processes, places, and things to internet for communication in and around the universe. The IoT objects focus both physical and logical things. The logical things include process, framework, applications, software, and program, and the physical things include people, places, physical entities, and devices. The data of such physical and logical things constitute a comprehensive IoT data base, where the structured, semi-structured, and unstructured data are available. In an IoT data base, ERP and CRM data are considered as structured data, XML data are normally considered as semi-structured data, and email documents, social web contents, pdf, ward, rich text documents are considered as un-structured data.

The study exposes in an IoT data base that around 80 % data are unstructured and having no pre-defined data models. Such un-structured data are textual, graphics, video, and symbols oriented. The spatio-temporal data having the facts or events with time-stamps are also a part of IoT database. The rapid increasing of IoT big data applications in today’s IoT world progressively lead to several problem issues such as, data volume, velocity, varieties, and value. Analyzing and inferencing cognitive values (knowledge) from large scale IoT data base in a real-time basis is more challenging day by day with the extreme growing of volume, and varieties data that are associated with numerous IoT applications. Such IoT knowledge analytics and inference face a number of real-time problems such as, managing heterogeneous knowledge, transforming varieties data into knowledge, transforming knowledge into actions, transforming actions into cognitive decisions, and tuning the cognitive decisions to coordinate the IoT motivated BI applications.

The convergences of statistical and computational learning mechanisms have been researched to deal with the data science and knowledge analytic problems. Data science and knowledge analytic implements are also used for analyzing and exploring various operational tasks associated with the IoT big data submissions, such as-data transformation and analysis, data mining, knowledge discovery, semantic knowledge explorations, structural analysis, and many more. The machine learning technics are implemented in many areas of knowledge discovery and semantic knowledge analytics to explore the application intelligence.

In almost all IoT big data applications, a huge amount of data is dumped into the storage that are highly redundant and unsuitable for the purpose of data analysis, modeling, information transformation, knowledge production, and the decision generation. A survey conducted by Par Stream shows that 94% of the organizations surveyed are facing challenges in IoT big data elicitations and analytics, and 70% organizations think that, the IoT big data analytics help to make better and more meaningful decisions for BI- service organizations [11].

VI. CONCLUSION

In this paper, we discussed a Visual knowledge production edge along with an in-network analytic platform that can be a potential base to resolve BI-service extortions. In future issue we want to design the distributed analytic algorithms for real time BI-service applications in consort with its behavioral analytics implementation mechanisms. The practices encompass both theoretical and simulated research for Intellectual BI-service applications. The different contexts and processes are explored for knowledge discovery, representation, semantic analytic, and inferences. The real world applications are modeled through smart architectures, algorithms, and frameworks to accomplish the in-network knowledge analytic tasks.

VII. ACKNOWLEDGMENT

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