Live Data Analytical along Synergistic Cloud and Edge Computing within Wireless IoT Networks

[1]Sanjay Kumar N V, [2]Chaithra S, [3]Ashwini Shekar, [4]Tejaswini P R

[1]Associate Professor CS&E, [2]M-Tech 4thsem CS&E

KIT, Tiptur-572201

Abstract-Recently, big data analytics has received important attention in a variety of application domains including business, space science, healthcare, telecommunication and Internet of Things (IoT). Among these areas, IoT is considered as an important platform in bringing people, processes, data and things/objects together in order to enhance the quality of our everyday lives. However, the key challenges are how to effectively extract useful features from the massive amount of heterogeneous data generated by resource-constrained IoT devices in order to provide real-time information and feedback to the end users, and how to utilize this data-aware intelligence in enhancing the performance of wireless IoT networks.

Although there are parallel advances in cloud computing and edge computing for addressing some issues in data analytics, they have their own benefits and limitations. The convergence of these two computing paradigms, i.e., massive virtually shared pool of computing and storage resources from the cloud and real time data processing by edge computing, could effectively enable live data analytics in wireless IoT networks. In this regard, here we propose a novel framework for coordinated processing between edge and cloud computing/ processing by integrating advantages from both the platforms. The proposed framework can exploit the network-wide knowledge and historical information available at the cloud center to guide edge computing units towards satisfying various performance requirements of heterogeneous wireless IoT networks. Starting with the main features, key enablers and the challenges of big data analytics, we provide various synergies and distinctions between cloud and edge processing. More importantly, we identify and describe the potential key enablers for the proposed edge-cloud collaborative framework, the associated key challenges and some interesting future research directions.

Keywords: Big data, data analytics, internet of things (IoT), cloud computing, edge computing, fog computing, Collaborative Filtering.

I. INTRODUCTION

The current trend in the Internet world is to connect all the devices/objects/things to the Internet with the objective of enhancing the quality of our everyday lives, thus leading to the emergence of Internet of Things (IoT) [1], [2]. Big data may be generated from various environments such as e Healthcare environment, online business/e-commerce, broadband and multimedia contents, cloud radio access networks, and distributed storage/sensing [3].The complexity of big data generated from the IoT environment depends on the computational cost required in processing the data rather than the size of data itself. Besides, this massive amount of data needs to be transferred from the edge nodes to the cloud, leading to the need of enormous communication bandwidth which is precious and expensive natural resource.

Existing wireless networks are mainly designed by considering communication resources as the primary resources with the connection-oriented approach, and other resources such as computing and caching are considered as secondary [4]. The integration of these paradigms may lead to additional degrees of freedom in effectively optimizing the resources of communication systems. In this regard, it has become an essential requirement to take all the involved resources into account while designing future wireless IoT networks by exploiting the synergy among communications, caching and computing paradigms [4], [5].

One of the recent developments in the computing world is the Internet-based computing, called cloud computing, which provides an ubiquitous and on-demand access to a virtually shared pool of configurable computing and storage resources [6]. On the other hand, the concept of edge computing, also called fog computing,1 is receiving important attention in order to address some of the drawbacks of cloud computing [8]-[10]. A few works have recently highlighted the need of coordination between edge computing and cloud computing [8], [11], however, they do not consider various practical aspects of live data analytics in wireless IoT networks.

Starting with the basic features and key enablers of big data analytics, we discuss various challenges in performing live data analytics in wireless IoT networks. Subsequently, we provide synergies and differences between cloud and edge computing platforms. Then, we propose a novel framework for collaborative processing between edge and cloud computing along with some interesting applications. Subsequently, we discuss various key enablers, associated challenges and future research directions with the objective of stimulating future research activities in this emerging domain.

II. SYSTEM MODEL

Figure 2.1 illustrates the key technology enablers for big data analytics. In the following, we provide brief description of these techniques from the data analytics perspective. Stochastic models are probabilistic models and are usually used to capture the explicit features and dynamics of the data traffic. The commonly used stochastic models are Markov models, time series, geometric models, and Kalmanlters [15]. On the other hand, data mining approach tries to extract implicit information from the data-sets and transform this information to a known structure for further usage by employing suitable anomaly detection, classification, clustering, and regression analysis methods.

Machine learning techniques aim to create a functional relationship between input data-set and output actions, and are capable of performing predictions and decisions based on the input data without requiring the need of following static program instructions. These techniques can be broadly categorized into unsupervised, supervised and reinforcement learning, and they may comprise of various classification techniques, regression analysis and Q-learning techniques. In addition to the conventional machine learning techniques, several advanced learning techniques such as active learning, deep learning, and online learning can be utilized to extract useful information from incomplete or complex data-sets.

Active learning is mostly useful for partially labeled datasets while deep learning is suitable for modeling complex behaviors of heterogeneous data-sets [15]. On the other hand, online learning deals with learning in real-time and is useful for applications where data arrives in a sequential order. In terms of computing platforms, edge computing and cloud computing are considered as key solutions for handling big data analytics.

Fig. 2.1. Main technology enablers for big data analytics.

III. PREVIOUS WORK

Zhang and Qiu [8] used large random matrices as building blocks to model the big data arising from a 5G massive MIMO system that is implemented using software denned radios. Liu *et al.* [3] proposed a novel large-scale network traffic monitoring and analysis system based on a Hadoop platform. The connection between big data analytics and mobile cellular networks has been systematically explored. A broad overview of big data analytics based on random matrix theory. Next, an architectural framework for the applications of big data analytics in cellular networks was proposed.

IV. PROPOSED METHODOLOGY

In this section author need to mention his simulation/experimental research model with neat block diagrams and flow charts. In the proposed system, work addresses the question of how to predict fine particulate matter given a combination of weather conditions.

Therefore, this study aims to elaborate a statistical model to predict the pollution levels from the meteorological conditions. This statistical approach is based on data mining, which is searching for some patterns in raw big data in order to extract regularities that can be used to build a predictive model. In the proposed system by implementing the Collaborative filtering algorithm, mining all the previous data about the pollution details and predicting the next day's fine particulate matter of the environment.

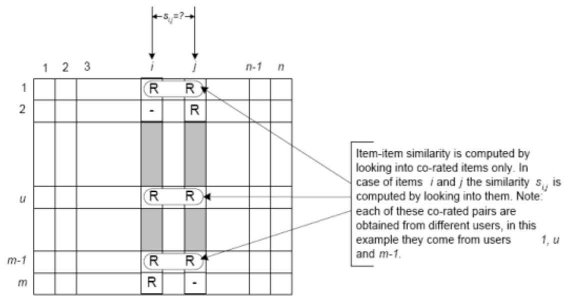

Fig. 4.1. Item-based Collaborative Filtering Algorithm Illustration.

V. SIMULATION/EXPERIMENTAL RESULTS

Figure 5.1 presents a generalized system model for collaborative edge-cloud processing in heterogeneous wireless IoT networks. In the proposed model, IoT edge gateways are equipped with cache memory and are capable of performing edge-caching in order to deliver the popular contents locally. The edge computing nodes may be any devices having the capability of computing, storage and network connectivity such as routers, switches, and video surveillance cameras. Depending on the application scenarios, IoT networks may comprise of various networks having distinct characteristics.

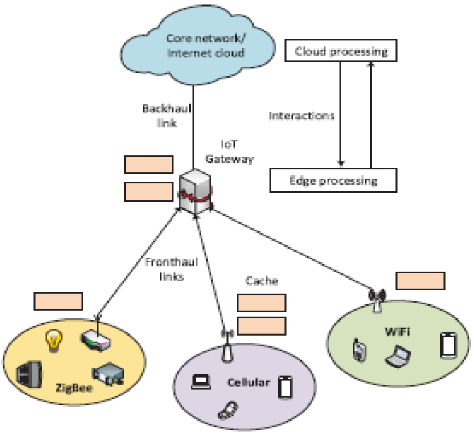

Fig. 5.1. Generalized system model for Collaborative Edge-cloud processing in heterogeneous IoT networks.

For example, in the smart home scenario, wireless IoT networks may consist of a Wi-Fi network, a Bluetooth network, a Zigbee network and a cellular network. The raw data coming from different domains/sensors is largely diverse and need to be collected over time. In addition, data dimensions and sizes may be different depending on the considered IoT application scenario. Besides the real-time processing of massive IoT data, this collaborative framework an enable new wireless IoT applications which may require collaborations among different edge computing units, and between edge computing units and the cloud centre.

The proposed system will benefit from the advantages of both the cloud computing and edge computing. In addition to this, we envision cloud centre as a monitoring and guidance platform to have effective real-time data processing at the edge-side of wireless IoT networks. In practical scenarios, IoT devices/sensors are heterogeneous in nature in terms of their computing capabilities, intelligence as well as the computing/ processing power. In this regard, it becomes highly beneficial to guide the operation/processing of edge-nodes in order to utilize the available communication and computing resources in an effective manner. In the considered framework, edge computing helps to gather information from the surrounding radio environment while the cloud computing assists by providing suitable instructions to the edge-side nodes for their operations. For example, the operations at the edge-side such as data compression, filtering, sampling rate, power control, and making decisions on the type of data to be sensed/acquired can be supported by the cloud centre by providing suitable control signals over the feedback links. Since the cloud centre can have a global view of information collected from a large number of sensors deployed over a large geographical region, the control of edge processing from the cloud-side can provide significant improvements in future wireless IoT networks. Due to huge amount of computing resources available at the cloud end, it is beneficial to offload much of the computational tasks to the cloud. On the other hand, it is advantageous to handle delay-sensitive tasks at the edge-side. Depending on various levels of information such as traffic types, location information, processing delay and transmission overhead, the decision on whether to offload data to the cloud or not can be made. It can also be considered that all the edge nodes are operated in a coordinated fashion in order to help each other in terms of communication, computing and storage/caching resources. Another important aspect which can be exploited in the proposed framework is that cloud processing can utilize the history/delayed information available at the cloud-centre in order to infer certain decisions for the edge processing without the need of waiting for the instantaneous data collected from IoT nodes.

VI. CONCLUSION

Cloud computing and edge computing are considered as two emerging paradigms in handling the massive amount of distributed data generated by IoT devices. However, these paradigms have their own advantages and disadvantages. Cloud computing provides a centralized pool of storage and computing resources and has a global view of the network but it is not suitable for applications demanding low latency, real time operation and high QoS. On the other hand, edge computing is suitable for the applications which need real-time treatment, mobility support, and location/context awareness but does not usually have sufficient computing and storage resources. Taking these aspects into consideration, this paper has proposed a novel framework of synergistic cloud-edge processing for enabling live data analytics in wireless IoT networks. The basic features, key enablers and the challenges of big data analytics in wireless IoT networks have been described and the main distinctions between cloud and edge processing have been presented. Furthermore, potential key enablers for the proposed collaborative edge-cloud computing framework have been identified and the associated key challenges have been presented in order to foster future research activities in this domain. Finally, it is worthy to mention that the proposed Cloud -edge synergistic framework can be exploited as an important platform for wireless networks to achieve various objectives such as dynamic spectrum management, energy efficient caching and offloading, closed-loop latency minimization, adaptive optimization of computing, communication and caching resources, even-driven resource allocation and security/privacy enhancement.

VII. FUTURE SCOPES

Finally, here we discussed some research challenges and big data analytics prospects for next-generation IoT networks. Future work is in progress to address the challenges faced by IoT networks to store enormous amount of data. By using computing fields such as cloud computing, edge computing, big data analytics, and Collaborative Filtering techniques, we have to work for the prediction of large amount of data in near future.

REFERENCES

[1] A. Al-Fuqaha, M. Guizani, M. Mohammadi, M. Aledhari, and M. Ayyash, ``Internet of Things: A survey on enabling technologies, protocols, and applications," *IEEE Commun. Surveys Tuts.*, vol. 17, no. 4, pp. 2347_2376, 4th Quart., 2015.

[2] S. K. Sharma, T. E. Bogale, S. Chatzinotas, X. Wang, and L. B. Le, ``Physical layer aspects of wireless IoT," in *Proc. Int. Symp. Wireless Commun. Syst. (ISWCS)*, Sep. 2016, pp. 304_308.

[3] P. Fan, ``Coping with the big data: Convergence of communications, computing and storage," *China Commun.*, vol. 13, no. 9, pp. 203_207, Sep. 2016.

[4] H. Liu, Z. Chen, and L. Qian, ``The three primary colors of mobile systems," *IEEE Commun. Mag.*, vol. 54, no. 9, pp. 15_21, Sep. 2016.

[5] S. Andreev *et al.*, ``Exploring synergy between communications, caching, and computing in 5G-grade deployments," *IEEE Commun. Mag.*, vol. 54, no. 8, pp. 60_69, Aug. 2016.

[6] J. Tang and T. Q. S. Quek, ``The role of cloud computing in content centric mobile networking," *IEEE Commun. Mag.*, vol. 54, no. 8, pp. 52_59, Aug. 2016.

[7] P. Corcoran and S. K. Datta, ``Mobile-edge computing and the Internet of Things for consumers: Extending cloud computing and services to the edge of the network," *IEEE Consum. Electron. Mag.*, vol. 5, no. 4, pp. 73_74 Oct. 2016.

[8] X. Masip-Bruin, E. Marn-Tordera, G. Tashakor, A. Jukan, and G. J. Ren, ``Foggy clouds and cloudy fogs: A real need for coordinated management of fog-to-cloud computing systems," *IEEE Wireless Commun.*, vol. 23, no. 5, pp. 120_128, Oct. 2016.

[9] C. Vallati, A. Virdis, E. Mingozzi, and G. Stea, ``Mobile-edge computing come home connecting things in future smart homes using LTE device-to-device communications," *IEEE Consum. Electron. Mag.*, vol. 5, no. 4, pp. 77_83, Oct. 2016.

[10] M. Satyanarayanan, ``The emergence of edge computing," *Computer*, vol. 50, no. 1, pp. 30_39, Jan. 2017.

[11] Shree Krishna Sharma, (member, *IEEE*), and Xianbin Wang, (fellow, *IEEE*), `` Live data analytics with collaborative edge and Cloud processing in wireless IoT networks", *IEEE* access (Volume: 5, march 2017)