Cloud-based Emerging Services Systems

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Abstract. The emerging services and analytics advocate the service delivery in a polymorphic view that successfully serves a variety of audience. The amalgamation of numerous modern technologies such as cloud computing, Internet of Things (IoT) and Big Data is the potential support behind the emerging services Systems. Today, IoT, also dubbed as ubiquitous sensing is taking the center stage over the traditional paradigm. The evolution of IoT necessitates the expansion of cloud horizon to deal with emerging challenges. In this paper, we study the cloud-based emerging services, useful in IoT paradigm, that support the effective data analytics. Also, we conceive a new classification called CNNC {**C**louda, **NNC**louda} for cloud data models; further, some important case studies are also discussed to further strengthen the classification.

Keywords. Emerging services, as-a-Service, analytics, cloud computing, IoT, Big Data, CNNC

1. Introduction

Emerging services and analytics promisingly hide the complex details of the comprehensive data processing from the end users and deliver a suave and plain results. The resulted outcomes are easily interpretable even by the technically naïve stakeholders (Chang, 2015; Chang et al., 2015), managers, and even a common user. The success of emerging services and analytics is largely depending upon the blending of various modern technologies and cloud computing, and IoT (Internet of Things) are just to name a few and are the core ingredients. The information age is shifting from traditional human-intervened Internet to Internet of Things (IoT) (Figure 1(a)), where the sensor embedded commodity, also called things, communicate among themselves (Chen, 2012) on the existing network resources and help facilitate the information collection and analytics with a very high degree of automation. The pool of IoT-enabled devices is growing rapidly and IoT footprint in increasing almost all in domains that includes trivial to complex applications such as smart grid (Monnier, 2013) to advanced smart cities (Zanella et al., 2014). The IoT “Things” include a diverse range of embedded objects or devices such heart monitoring implants, sensor equipped automobiles, thermostat systems and so on (Hwang et al., 2013). The increasing IoT maturity and the advancing cloud-based services are revolutionizing the information generation, collection, management and analytics. In IoT realm, the devices collect useful data and then share the data between other devices (Farooq et al., 2015); there are 9 billion such devices that exist today and the number is inflating. Evans (2011) believes this number will reach nearly 50 billion by year 2020 (Figure 1(b)), which substantiates the fact that the permeation of IoT is expanding in human life. This indicates that the number of new applications under IoT umbrella is increasing and consequently a massive amount of data is being generated at swift rate, called Big Data (Villars et al., 2011), where the social media and sensor embedded systems play central role in data inundation. As, the IoT-enabled devices access and process the data from several peer devices to constitute immediate decisions and swift actions, there is a continuous need for equally strong data model, equipped with robust data engineering and comprehensive analytical capabilities as the traditional data models are becoming inadequate in meeting the growing challenges that information-rich IoT evolution possess.

To appropriately accommodate and adequately address the growing IoT data challenges, the concept of cloud computing framework has emerged as a globally acceptable solution for secure and efficient data engineering and functionally-rich analytics for technically naïve stakeholders, director, managers to tech-savvy users. The backbone of the widely successful cloud adaptation is the secure and robust existing or evolving services that are delivered in the form of **-as-a-Service* and the state of the art as-a-Service cloud modality has gone beyond the core Infrastructure-as-a-Service (IaaS), Platform-as-a-Service (PaaS), Software-as-a-Service (SaaS), and Database-as-a-

Service (DBaaS) (Curino, et al., 2011; Seibold and Kemper, 2012) and this paper highlights some of them that are highly relevant in IoT context.

Today, a trend of migration, from on-premises to cloud environment, of applications from almost all possible areas is increasingly being observed to utilize the best offered services at substantially reduced cost of cloud computing; the progressive maturity of IoT is accelerating this migration. The need for the efficient and successful management and computation of the scalable Big Data motivates the scientific communities to devise and develop the new scalable systems. Consequently, the appeal introduces and inducts a high abundance of cloud and non-cloud data models; it becomes nearly impractical for a user to thoroughly access such a large set of data models to understand individual's technology in search for the most suitable cloud model. In this work, we harness the scientific name of the data models and introduce a novel CNNC {**C**loud**a**, **NNC**loud**a** | a- assisted, NN- No Name} classification. The CNNC classification is based upon the intuitiveness of the scientific name of the cloud data model and considers two types of cloud data models -1) the model contains the term "cloud" in their name (Clouda), and 2) the model doesn't have the word "cloud" in its name at all (NNClouda). In addition, some interesting case studies are also explored to further strengthening the core of CNNC classification amid the broadening spectrum of emerging services and analytics in IoT age.

Rest of the paper is structured as follows. Section 2 provides a brief overview of the emerging Services and analytics. This section expands on the concept of cloud computing and IoT. Also, explored are some of the emerging analytics techniques. Section 3 elaborates on the novel CNNC classification and investigates some key data models of Clouda and NNClouda type to further understand and validate the proposed classification. Section 4 discusses some interesting case studies, focusing on the undertaken cloud models. Section 5 highlights on some emerging cloud services, which is followed by the extended discussions on emerging services and analytics in section 6. Section 7 explains the impacts and benefits of this work to businesses. Finally, the paper is concluded in section 8.

2. Emerging Services and Analytics: Brief Overview

This section provides the brief overview of some core components of emerging services and analytics. The discussion on the emerging cloud services is elaborated a bit comparatively.

2.1 IoT

IoT is a network constituted by uniquely identifiable commodity objects or devices equipped with some sensing system (Ashton, 2009). IoT paradigm promotes a seamless amalgamation between the smart devices, scatter around us, and the physical world to ensure full automation that eventually ameliorates human life. Some of the examples of IoT-enabled commodity devices or things include heart monitoring implants, automobiles with embedded sensors, firefighter' devices, smart thermostat systems, and Wi-Fi enabled washer/dryers (Sundmaeker, 2010). As the arena of IoT is expanding, the number of IoT-enabled applications is also rapidly growing, which results in massive growth of smart devices in multiple order comparatively (Figure 1(b)). This swift increase in the number of sensing things is responsible for generating and storage of a plethora amount of Big Data at much faster rate. The data needs to be engineered and analyzed, which require robust services and analytical systems as the traditional techniques unable to successfully and efficiently accost such data stress.

2.2 Big Data

IoT paradigm is increasingly encouraging the ubiquitous connectivity of the intelligent objects within internal or external world. The continuous rapid growth of large number of IoT-enabled objects and storage technology have resulted into the massive amount of heterogeneous digital footprints and sizeable traces. A vast amount of data (IBM, 2012) is being generated by various sensing sources every day. The actual pattern and nature of such data is indistinct, but is certainly large, complex, heterogonous, structure and unstructured (O'Leary, 2013). Palermo (2014) demonstrates some important attributes of Big Data such as volume, variety, and velocity and some core constituents of IoT like sensor-embedded devices, intelligence for quick decision making, and connectivity for data sharing. Also, the rapid growth of sensing devices under IoT purview is generating such a large scale complex and heterogeneous data that the available computing capacity of the existing systems (Figure 2) unable to successfully match up the data challenges and today, this has emerged as one of the core issues for the data science community

(Manyika et al., 2011; Hilbert and López, 2011). The storage capacity and also the processing power of the existing data computing systems are failed in handling the stress of Big Data.

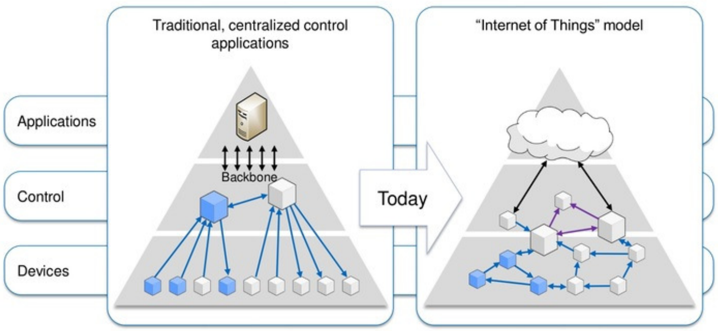

Figure 1(a). Traditional vs. IoT paradigm
(Source: db.in.tum.de/teaching/ws1314/industrialIoT/)

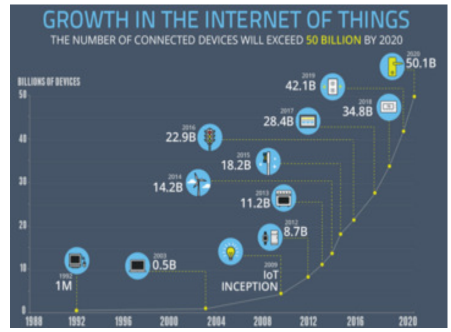

Figure 1(b). IoT growth over years
(Source: www.ncta.com/broadband-by-the-numbers/)

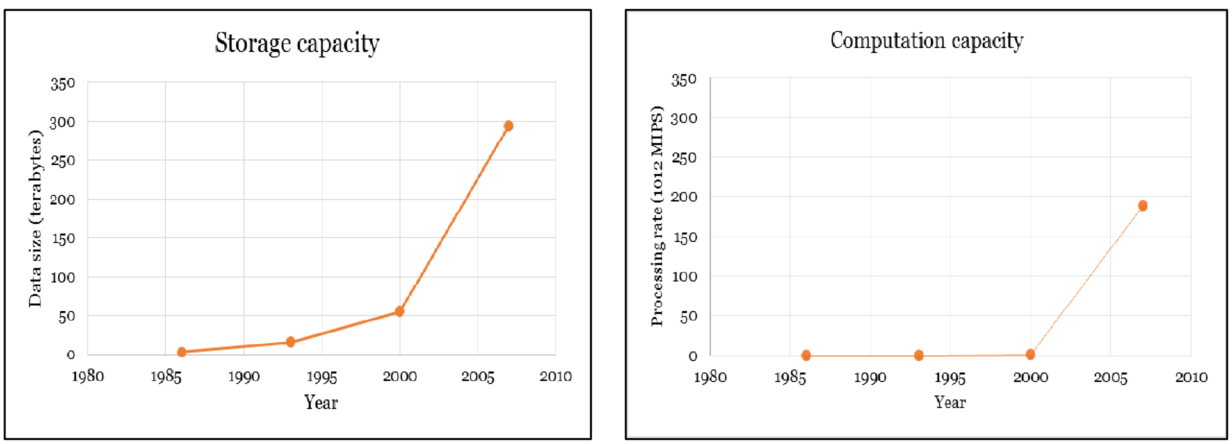

Figure 2. Storage vs. Computation capacity (Source: Hilbert et al., 2011)

As IoT and its applications are majorly impacting the human life, the scientific communities contemplate a broader outreach from the processing and sharing of Big Data across the variety of the several commodity devices around us. Consequently, the development of new capable services and analytics is encouraged to cater the current data processing and presentation need. The exploratory analysis of the various aspects of Big Data in cloud can help in understaing its important characterstics (Nugent et al., 2013) that may be very valueable to stakeholders and managers. Sharma et al. (2014, 2015a, 2015b) provide the elaborated discusisons on the characteristics and complexities of Big Data.

2.3 Cloud computing

Cloud computing has emerged as a ubiquitous paradigm for the service-oriented computing; it is believed to overcome the bottlenecks, experienced by the traditional computing systems when deal with the dynamics, complexities and uncertainties of the modern IoT-inclined data-oriented enterprise applications. Over the years, the basic cloud paradigms -- Infrastructure-as-a-Service (IaaS), Platform-as-a-Service (PaaS), and Software-as-a-Service (SaaS) that have attained significant popularity and in the IoT age, a new paradigm- Database-as-a-Service (DBaaS), also getting popular. Elasticity in service usage and consequently price (pay-per-use), low financial inputs upfront, reasonably reduced time to market (TTM), responsibility shift in risk management, etc. are some of the potential convincing attributes of cloud computing. Cloud computing is a monetarily affordable, and technologically powerful innovation that is developed for overly complex and excessively large computations; that renounces any need for a dedicated space, and on-premises management of expensive hardware infrastructure and delicate software systems and figure 3 depicts the popular base cloud services.

- **Software-as-a-Service (SaaS)**: SaaS is one of the most popular, repository-rich and widely used cloud model that is offering the services for more than a decade now. The service repository is much diversified and cover a very wide range of simple to complex services such as Google Email, Google Doc, etc. Under the contractual agreement of SaaS model, the vendor also called the service provider is fully responsible to provide all the essential infrastructure consisting of the robust hardware resources and expansive software systems. Also provided is a graphical user interface (GUI) that facilitates the user interaction with the service.

- **Infrastructure-as-a-Service (IaaS)**: As, the name suggests, IaaS offers the infrastructure as service. The infrastructure consists of various building blocks, which can be combined or layered to derive a customized environment most appropriate to execute the designated applications. Some of the most popular examples of IaaS cloud model include Amazon Web Services (AWS), Rackspace, etc.

- **Platform-as-a-Service (PaaS)**: In the PaaS cloud model, the service provider is responsible to provide the risk free and robust environment for software product development. The environment consists of required software tools and is hosted on the hardware infrastructure of the service provider. A user can avail the benefits of the PaaS for the software development, either by using the APIs provided or thorough a GUI. Google App Engine, Force.com, etc. are some of the popular example of PaaS.

- **Database-as-a-Service (DBaaS)**: The DBaaS cloud model (Curino, et al., 2011) is gaining popularity in this data science age (Wolfe, 2013). The service agreement under DBaaS assures the shift of data management related responsibilities, especially administration from end user to a third party vendor, called service provider, who can be public or private. Some of the data related operational burdens include upgrade, provisioning, failover management, configuration, seamless scaling, performance tuning, backup, privacy, access control (Seibold and Kemper, 2012), etc. DBaaS not only migrates the responsibilities, but it guarantees overall a very lower costs to the end users. Also, on the client site, the DBaaS model avoids any needs of a professionally trained database administrator (DBA) who is primarily responsible of data management and maintenance otherwise. In DBaaS, the engineers, engaged in application development are neither expected nor required to have expert understanding of database management. The data related operations such as failover, scaling, etc. in DBaaS cloud is expected not to impact any live user.

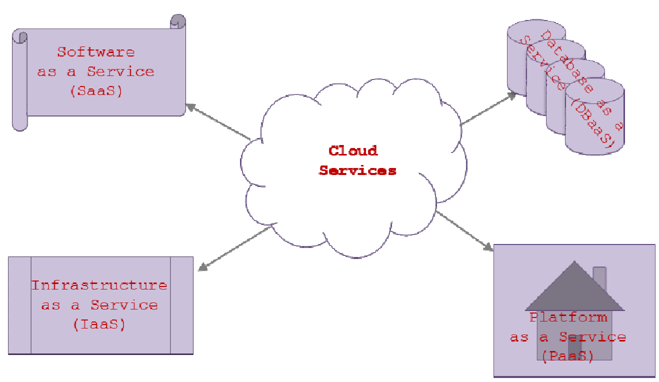

Figure 3. Base cloud services

2.4 Integrated cloud computing and IoT ecosystem

The growing smart communication among the things, especially the sensor equipped, under the purview of IoT is resulting into production of incredibly large amount of Big Data. Supported by the context-aware computing, Big Data is sufficient enough to address the nontrivial and comprehensive tasks with great degree of automation regardless the disciplines - financial, health, automobile, etc. Soon, the concept of IoT is going to deeply pervade through the human life intending to automate the routine chores. The ubiquitous sensing of all the devices around us emits enormous quantity of Big Data that needs to be stored, computed and visualized and analyzed in efficient manner. Today, cloud computing is the most recommended solution for above mentioned issues of Big Data that promises to deliver the efficient services as traditional commodities. The emerging cloud services are being appreciated for supporting the analyses of Big Data for naïve to elite experts such as stakeholder, mangers and data scientists for their routine tasks. The needs for the highly robust computing and analytical services to address and analyze the data-related challenges with the exceedingly reduced cost have further brought the service-rich cloud computing to forefront. The rising interest in IoT and cloud provisioning system has triggered the surge in cloud-housed comprehensive analytics. In this paper also, we have illustrated some important related cloud-based analytic services that are highly efficient for the dedicated tasks and data intensive applications, they have been developed for; gene structure prediction, image processing, predicting the relationship of customers and their purchasing patterns and web searches are some good examples of such data-rich applications and for the required appropriate analytical services to analyze their highly complex and heterogeneous data cloud is the pertinent choice from the security, efficiency and affordability aspects. Academia, industry and research communities are rapidly developing robust analytic frameworks and housing them in cloud environment, and are delivered and utilized as analytics-as-a-Service. In 2008, to deal with the collaborative complex computations, instead of data in the cloud, Cerri et al. (2008) devised an analytical framework in cloud, called knowledge in the cloud that delivered multifarious knowledge. Figure 4 shows the cloud computing and IoT ecosystem. It can be noticed that a sensing system, may differ in attributes, is embedded into the objects /devices around us. The device communication with cloud is facilitated through the robust cloud services. However, in IoT infrastructure a smart connectivity gateway, may be with the existing networks, is required to further strengthen the device communication.

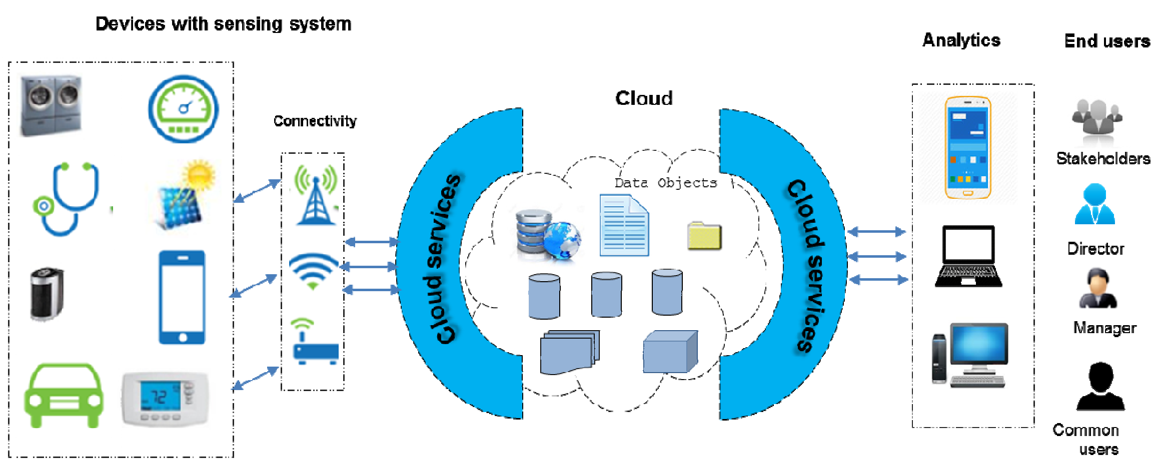

Figure 4. Cloud computing and IoT ecosystem

The devices proactively generate the heterogeneous Big Data, which is housed in the cloud in various formats and is available for analysis through robust cloud services. Therefore, the communication between the cloud and the external word is feasible only through robust and reliable cloud services.

2.5. Machine learning and predictive analytics

Machine learning and its supported predictive analytics provide the intelligent and efficient processing of data and, the wide usage of these analytical technologies has brought them to fore in data science, especially for the new incarnation of data into Big Data. The machine learning algorithms help recognize the subtle association of the variables in the dataset, and satisfying all the input criterions, the analytical systems quickly deliver the output, presented in the desired form that is easily interpretable by the end users or stakeholders (Chen and Zhang, 2014). The predictive analytics are highly sought in business domain in the view to elevate the product sale. These techniques are useful in predicting the items types, a customer may be interested to buy and the associated approximate spending (Kumar, 2008). As the customer behaviors is closely predictable using the predictive modeling and this enhances the expansion of the business opportunities and also the customer may be recommended and served with special offers and discounts.

2.6. Agile methodology

The stakeholders always desire to have the even the comprehensive software products ready in a shorter time. Also, the functional or visual requirements related to that specific product from the stakeholders change several times over the span of that product development. To accommodate all such limitations, restrictions, and complexity and to promisingly deliver the robust software systems in smaller time span, standard agile development is highly efficient (Zhang, Cheng, and Boutaba, 2010).

2.7. Statistical analytics

The evolution of data science in the form of Big Data has brought the statistical analytics to forefront regardless the domain. The stakeholders are applying the statistical approaches on their customer databases to derive useful and accurate recommendations to improve their business. Also, some statistical frameworks such as R programing have gained unexpected popularity due to its rich set of statistical libraries; which are capable to produce the quick results and their ability for swift, effective and on-the-spot variation in presentation as desired by the end users or stakeholders. Also, regression testing is one of the highly sought mechanism in statistical analysis along with the easily interpretable presentation of the crucial outcomes (Antcheva et al., 2009; Miner et al., 2009).

2.8. Visual analytics

With the recent advancements of data science, where data has taken a more complex shape in the form of Big Data, visual analytics have become extremely relevant to deliver the elegant and informative presentations of the highly complex data processed for the end users. Visual analytics also come equipped with some sophisticated statistical models to be used by the end users or stakeholders (Antcheva et al., 2009; LaValleet al., 2013) to obtain the desired interpretation. In business domain, the visual analytics are extremely used to envisage the market and business trends and customer shopping behavior in order to improve the future decision making to elevate the business.

3 CNNC Classification for Emerging Services Models

With the growing projection of IoT smart, embedded, and sensing devices (Evans, 2011), the number of available cloud-powered models for Big Data management is increasing; every month, the inclusion of several new models is being obviously observed and claim to deliver the effective solutions when deal with Big Data. As the number of the cloud providers is rising, it becomes nearly impossible for a cloud-interested user to surf through that giant pool of models to comprehend their technology and suitability for his/her purpose, especially from cloud aspect of IoT. In this case, it is very likely that a user fails to hit the most pertinent model due to several reasons such as gradually eroded user patience, restricted time availability, etc.

In such scenario, to assists the user, we focus on the name of the cloud models and propose a novel first-level classification, called CNNC. The objective of this classification is to gauge the intuitiveness of the name of the cloud models.

The CNNC classification is believed to reduce the search time and consequent pain of the user to a greater degree. Only the cloud-powered data models are eligible for this classification. The scientific names of the cloud-assisted models are considered as the basis for classification, and are divided into two categories -- **C**louda and **NNC**louda.

CNNC = {**C**loud**a**, **NNC**loud**a**}, where NN- **N**o **N**ame, a- **a**ssisted

We further mature and test the proposed CNNC classification, by applying and explaining it with some prominent cloud-powered IoT- Big Data models. We believe, the discussion of this classification will invigorate the communities for more intuitive naming convention, where only the scientific name of a model itself is merely sufficient to gesticulate about underlying cloud technologies.

3.1 Clouda (Cloud-assisted) models

Definition 1. Clouda represents that class of data models that have the term “cloud” in their name.

Hypothesis 1. All cloud-powered Big Data models have the word “cloud” in their name.

To validate this hypothesis, we review some cloud-supported Big Data models of Clouda nature.

3.1.1 CloudKit (Cloud): The CloudKit framework (Hanson, 2015) is a new technology that is meant to be used as service for data transportation with (to/from) cloud. CloudKit is not a local storage rather is a transport mechanism that is used as the Rack middleware. It provides an auto-versioned RESTful JSON storage that has no schema restriction. Although, it is a middleware component for Rack-assisted applications but, can be used on its own.

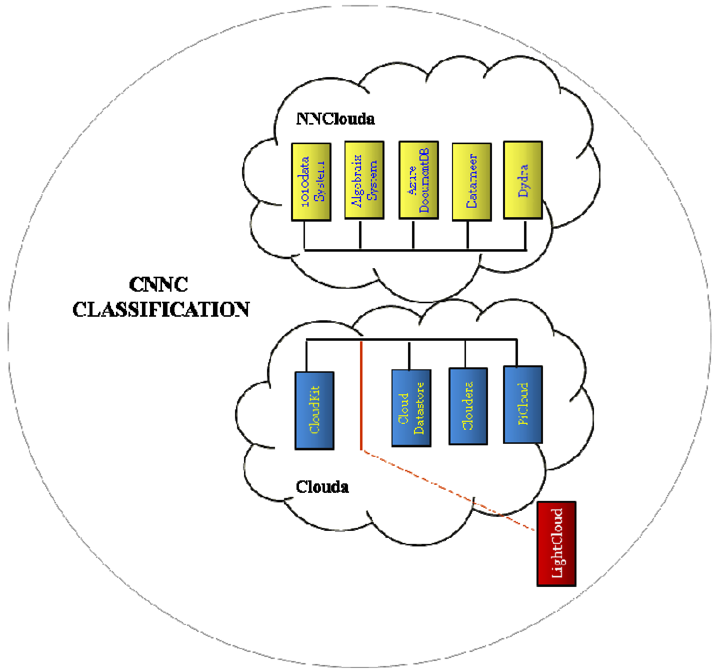

Figure 5. CNNC classification for emerging service models

3.1.2 Cloud Datastore (Cloud): Cloud Datastore (Google Inc., 2010) is a NoSQL datastore to store the schema-free, non-relational data in cloud. Each instance of the Cloud Datastore is entirely managed by Google Inc. Cloud Datastore experiences no downtime and the data is replicated across multiple datacenters, hence high data availability. Also, the Cloud Datastore scales up automatically for growing data traffic, endorses ACID transactions, and offers eventual consistency for queries.

3.1.3 LightCloud (Non-cloud): LightCloud (Plurk.com, 2009), built on Tokyo Tyrant (FAL Lab, 2010), is an open source, distributed key-value database that is always compared with memcached from performance point of view. It is tested for storing millions of keys on a very small group of few servers. However, in contrast to memcachedb (Chu, 2008), the LightCloud is horizontally scalable with master-master replication architecture and commodity hardware nodes are easily added to achieve it. Although, Salihefendic (2009) in his blog quotes about the LightCloud as “*Plurk's open-source cloud database LightCloud…,*” but, the available documentation on LightCloud does not confirm the LightCloud reliance on cloud.

3.1.4 Cloudera (Cloud): Cloudera lately has drawn widespread attention for its completely open source, Apache Hadoop distribution, popularly known as CDH (Cloudera’s Distribution for Hadoop) (Cloudera, 2012b). CDH is a regressively tested distribution for Apache Hadoop, which has been widely deployed with extensive outreach. CDH is one of the most complete solution for Hadoop, which provides to the end users the batch processing of the massive data, support for MapReduce inclusion, interactive SQL and search, etc.

3.1.5 PiCloud (Cloud): PiCloud (Elkabany and Staley, 2014) provides a cloud computing environment that helps the users to avail the massive computational power (thousands of cores) from Amazon Web Services (Cloud, 2011), by completely avoiding the management, maintenance, or even configuration of the virtual servers. The access to the PiCloud interface is feasible using 1) a command line, 2) a Python cloud library, or 3) web base GUI and can be customized to accommodate other programming languages, though, Python is the default.

3.2 NNClouda (No Name Cloud-assisted) models

Definition 2. NNClouda is the representation for that class of Big Data models, which are cloud-powered, but do not have the word "cloud" in their name.

Hypothesis 2. The cloud-powered models not necessary to have the word "cloud" in their name.

In order to investigate the hypothesis 2, we analyze some of the data models of NNClouda class; the data models should not contain the word cloud in their name but must be cloud-enabled.

3.2.1 1010data System (Cloud): The 1010data (Bloor, 2011) is a columnar database system that has advanced dynamic in-memory capability. It is a cloud base solution that best avails the massively parallel processing for data management. It is a suite of advanced analytics that is devised and designed to perform the analytics exactly on the designated data elements, which are intended to be analyzed. The data is comprehended in orderly fashion and in the inherent structure, producing the efficient results.

3.2.2 Algebraix System (Cloud): ALGEBRAIX (Silver, 2005) is a cloud technology that harnesses the power modern computer architectures and offers such a robust data analytics operations for Big Data, which are not possible in the confines of conventional database systems, which are inflexible and inefficient to address the Big Data challenges. The ALGEBRAIX uses the full potential of mathematical models and maintains a universe of algebraic expressions relating data. The data is loaded in its native format and operations are performed on the same.

3.2.3 Azure DocumentDB (Cloud): Azure DocumentDB (Microsoft Azure, 2015) as a whole provides an enterprise-proven hybrid IaaS and PaaS cloud infrastructure where DocumentDB serves as a NoSQL document database, which inside the database engine natively supports JSON and JavaScript. DocumentDB is born in the cloud and backed by blazingly fast, low-latency, write-optimized, solid-state drive storage. Being a cloud platform, Azure DocumentDB can be scaled up or down quickly according to the user's requests and demands.

3.2.4 Datameer (Cloud): Datameer, Inc. (Groschupf, 2009) provides cloud based (PaaS) effective, self-serviced, and schema-free analytics and visualization support for Big Data application for Hadoop. It also offers the deployment- specific SaaS Big Data analytics platform. Datameer is highly scalable up to thousands of nodes and all major distributions of Hadoop can best use it. Datameer provides a cost-effective Hadoop-as-a-Service (Schneider, 2012) platform and Datameer Analytics Solution (DAS) is one of the popular services that Datameer offers. This avoids the on-premises overly complex configuration and deployment of Hadoop and therefore, helps the business executives and managers to stay dedicated to analytics only and utilize their time much effectively.

3.2.5 Dydra (Cloud): Dydra (Anderson, et al., 2011) is a fully managed cloud based graph database, which, natively stores the data as a property graph. The property graph clearly shows the relationships, if any, in the underlying data. Dydra is a very useful solution for a vast variety of IoT-enabled Big Data applications as most of the problems are reducible to graphs with little or more efforts. Dydra is a multi-tenant data store and query engine. Dydra allows the data operations through the query language, called SPARQL. It is an industry-standard, which specifically devised to query the graph databases such as Resource Description Framework (RDF) (Pan, 2009).

Validation of hypotheses. With the help of the exploration of cloud-powered models, we examine the correctness of both the hypotheses. Figure 5 provides a glimpse of CNNC classification, where the element Clouda is useful in validating the 1st hypothesis, and other constituent NNClouda will be helpful in testing the validity of hypothesis 2.

In figure 5, it can be observed, out of all the children of Clouda, at least one child, LightCloud is dissimilar from rest of its siblings. The LightCloud model has on-premises data storage and operations, in contrast to its other siblings, which believe in cloud-enabled storage. According to the hypothesis 1, the cloud-powered data models have the word "cloud" in their name, however, the investigation on Clouda class discovers that explanation of LightCloud is unable to validate this hypothesis; the LightCloud (Light + "Cloud") model has the word "Cloud" in its name, but is not cloud-powered at least yet, rather perform on-premises data storage and related computations and therefore, fails the hypothesis 1. The investigation on NNClouda category discloses that all its children, examined in this paper are cloud-powered and not any of them has the word “cloud” in their scientific name; this fact correctly validates the hypothesis 2.

4 Related Case Studies

In this section, we briefly survey some of the modern and important case studies that discuss and further substantiate the widening bandwidth of cloud computing into IoT and Big Data, especially Big Data. The case studies are selected from numerous public and private areas such as healthcare, IT software and hardware, media, eservice, ecom, gaming, space, etc., in order to procure the better investigating outcomes with diversified projection.

4.1 CDC (Public health): The Centers for Disease Control and Prevention (CDC) always strive to improve public health concerns (Kass-Hout, 2013). Lately, CDC started a health awareness program, called BioSense 2.0. The goal is to provide the national, state or local level awareness about all the health-related threats and their appropriate responses. To bypass the financial burden of purchasing costly hardware infrastructure and software systems, and to avoid the involved complex configuration, CDC adopted Amazon Web Service (AWS) cloud. Which provides the low cost operations with pay-per-use scheme. Also, the hosted systems are high available. The cloud has full support for the security and practice compliance.

4.2 DellSecureWorks (IT services): Dell SecureWorks, with global headquarters in GA, USA, is an information security services industry that protects thousands of customers against cyber threats and attacks all around the globe (Cloudera, 2012a). Dell SecureWorks collects and analyzes the information on millions of simultaneous IT events occurred globally in a few milliseconds. Dell SecureWorks operates round the clock and provides real-time security for the IT related assets of its clients. In order to provide and maintain such promising services, Dell SecureWorks has to process enormous data on high-end technologies, demanding high cost. Cloudera offers Dell SecureWorks a better solution that address the data processing challenges. The solution is highly cost-effective and speedy for storing, scaling, and analyzing the massive amounts of information in real-time.

4.3 Expedia (Eservice)**:** Expedia, Inc. (Kobashigawa-Bates, 2010) is one of the world’s largest online travel agency, consisting of numerous popular brands such as Hotels.com, Hotwire.com, etc. in more than 60 countries. Along with the other operations, the direct bookings to travel suppliers, and advertising opportunity are highly popular and the company experiences heavy traffic every day. Expedia also powers its partners the same services. Observing a regular increase in through traffic, Expedia moved to use Amazon Web Services (AWS) in 2010 to avail the global infrastructure to support Asia Pacific customers and to solve key issues such as automation, and customer proximity, etc. By 2011, Expedia shipped its several high-volumes critical applications to AWS and Global Deals Engine (GDE) is one such example; GDE administers the deals with its online partners and allows them to use Expedia APIs and other tool tools for various purposes.

4.4 NASA (Space)**:** National Aeronautics and Space Administration (NASA) has numerous centers around the nation. Jet Propulsion Laboratory (JPL) is one of the premier centers that is constantly engaged in the robotic exploration of space (Cureton, 2012). It has launched the robots to every planet in the solar system. It gathers huge amount of imagery data, being pumped by the robotic sensors. For the Mars Exploration Rover and the Mars Science Laboratory, the successful missions, NASA/JPL started to the Amazon Web Services (AWS) cloud is an essential part of the tactical operations to capture and store the images and metadata collected. Also, NASA planned to share the thrilled success and experience of Mars mission with the interested population around the globe. Hence, it decided to make the most current up-to-the-minute details of the mission, especially during the final 7 minutes, rover took to descend through the Martian atmosphere and land on Mars. So, JPL used AWS again to stream the landing images and videos. Considering the fact the public users, spread all over the globe, would be visiting its websites, NASA decided to served its contents from AWS clusters, situated around the world. This helped to meet the global demand of heavy traffic experienced by websites and also offered enhanced the viewer’s experience.

4.5 Netflix (Media)**:** Netflix, founded in 1999 and based in California, supplies the Internet streaming media on demand to the users (TSE, 2015). The viewers almost all around the globe enjoy the subscription-based services of Netflix. The major market includes the countries such as North America, South America, Australia, New Zealand, Denmark, United Kingdom, France, etc. The content can be streamed online anywhere internationally. However, in

United States, the flat rate DVD-by-mail system is also available, where the mailed DVDs are dispatched via the Permit Reply Mail. Today, Netflix offer a collection of way more than 100,000 titles on DVD and has greatly surpassed 10 million subscribers. The scalability of the subscription and the competitive pressure for supporting other media devices such as tablets, iPhones, etc. are some of the leading factors that compel Netflix to explore the advance solutions that promise the seamless global service. Netflix finally believes in Amazon Web Services (AWS) for services and content delivery. AWS cloud has powered Netflix to deploy thousands of servers and terabytes of storage in almost no time.

5 Emerging as-a-Service and Analytics Models

IoT can be understood as a pervasive system that may have more than one mesh of embedded sensing devices. In coming years, the IoT paradigm is expected to encompass the scalable networks of billions of uniquely identified devices, also called things. The devices are highly capable for sensing, computing, communicating, uniquely identifying the other peer devices for communication and effuse humongous data streams; therefore, the IoT paradigm triggers the emission of amassed data, where swift inclusion of cloud-based services and analytics becomes indispensable in order to harness the full potential of the data and discover valuable knowledge, insight, and complex relationships between variables of the data. The functionally-rich cloud-based services and analytics help shifting the data engineering and computation burden from the end entity to the cloud environment and hide that complex details from the end users. This greatly eases the analysis process, especially for technically naive stakeholder, director, managers, or even for common users. Therefore, in recent years, the communities have focused on the development of the cloud-supported services and analytics to deliver the customizable outputs that suffice the needs of various types of users. In this section, we briefly illustrate some of the cloud-based emerging services and analytics, which may be highly useful in growing IoT paradigm.

1) **Business Integration-as-a-Service (BIaaS/BIaS)** enables the connections between numerous cloud-powered services and combines various other services and business activities to achieve a streamline process (Chang et al., 2012; Chang, 2013).

2) **Business Intelligence-as-a-Service (SaaS BI/BIaaS)** is an emerging cloud-supported service and analytics that efficiently facilitates the business intelligence exercise and provides the data retrieval through a web resource. SaaS BI/BIaaS is highly useful to stakeholders, managers, and tech-naïve common user and it completely hides the implementation details and presents the simple abstraction, thus elevate performance, to them (Sano, 2014; Chang, 2014).

3) **Business Framework-as-a-Service (BFaaS)** is a cloud assisted solution for business organizations to embrace the cloud-based services and practices. BFaaS is capable for providing the right strategies and business cases, accurately reviewing business performance in cloud, resolving the desktop to cloud migration issues and among heterogeneous clouds from several distinct providers, and smoothly synchronizing between IaaS, PaaS, SaaS and business entities and between cloud-related disparate research methodologies (Chang et al., 2013).

4) **Cloud-Based Analytics-as-a-Service (CLAaaS)** delivers a data analytics, housed in the cloud as service to users. CLAaaS also facilitates on demand data storage and multifarious analytics using the customizable user interfaces. Also, for different user group, the interfaces can be customized differently or uniquely for query, decision management, and workflow design and service execution (Zulkernine et al., 2013).

5) **Data-as-a-Service (DaaS)** is a cloud-based relatively new service that on demand delivers the data to consumers using the existing or new APIs. The use of DaaS helps avoid the typical need of - 1) storage and retrieval of behemoth data assets, and 2) exhaustive searching in that colossus data assets in order to derive the useful knowledge and statistics (Vu et al., 2012).

6) **Data Integrity-as-a-Service (DIaaS)** gauges the criticality of some data-oriented well-known issues; and therefore, to address them appropriately, it combines all the expertise essential for data integrity. Public verifiability and dynamic content are few such examples where DIaaS is highly useful. DIaaS shreds off the

burdens of managing data integrity from a storage service as it manages the data integrity using a third party independent data integrity management service (IMS). Also, the inclusion of IMS helps reduce the security risk of the data stored in the storage services as now IMS checks the data integrity (Nepal et al., 2011).

7) **Data Mining-as-a-Service (DMAS/DMaaS)** offers the data owners to utilize the hardware and software solutions dispensed by DMAS/DMaaS providers and discourages them for the development of their own. DMAS/DMaaS is specially effective and useful for those consumers who govern mountainous amount of the data, but short in budget, allocated for data analysis. For such consumers, to outsource their data and data mining operations to a third-party service provider that always raises some security and monetarily concerns, but DMAS/DMaaS avoids the needs of any third-party service provider (Liu et al., 2012).

8) **Database-as-a-Service (DBaaS/DaaS)** is one of the most sought cloud-based emerging services in recent times to address the swiftly grown market needs due to the data inundation from IoT and other outlets. DBaaS/DaaS is highly effective in shifting much of the operational efforts such as provisioning, scaling, performance tuning, backup, and privacy to service providers in cloud from the localized database owners, administrations or users. Thereby, it guarantees lowering the overall expenditure as compared to the on-premises operational cost. Amazon RDS and Microsoft SQL Azure are the early providers of DBaaS (Curino, 2011).

9) **Ethernet-as-a-Service (EaaS)** is a cloud service that has high-bandwidth and fiber optic. It uses a two-way broadband shared infrastructure to successfully provide ubiquitous connectivity to remotely located devices (Zaslavsky et al., 2013).

10) **Failure-as-a-Service (FaaS)** is a cloud-based service that is useful in performing the routine large-scale failure drills in real deployments. FaaS is capable to regularly conduct the large-scale failures online. Thereby, it may further strengthen the ability to anticipate, mitigate, respond, or recover from failures at individual or organizational level (Gunawi et al., 2011).

11) **Forensics-as-a-Service (FRaaS)** provides a comprehensive cloud-powered forensics solution to develop a repeatable system. The system could be developed as a standard forensics operational model for the deployment in cloud irrespective of the client service lines or environments (Shende et al., 2012).

12) **Identity and Policy Management-as-a-Service (IPMaaS)** a cloud-supported service, dedicated for the policy management. It is conceived to deliver a unified control point the users, where they are capable to manage and access the policies and to control the access to their resources regardless the stored location of these assets (Takabi et al., 2012).

13) **Mobility-as-a-Service (MobiaaS)** is a cloud-enabled service that is highly useful in providing the required connectivity service continuity to the consumers. It also capable to deliver seamless handover for flows like voice as the consumers use a multitude of devices to communicate (Baliga et al., 2011).

14) **Object-as-a-Service (ObaaS)** is based upon the idea to dynamically build the service on each object as demanded and subsequently integrate that into the whole composition. ObaaS executes on the objects and exploits its sensing, actuating, and computing capabilities (Cherrier et al., 2014).

15) **Security-as-a-Service (SecuaaS/SaaS)** provides the cloud-based solution for data, host and application protection. SecuaaS/SaaS is capable to validate and ensure the security aspect over a geographically sparse scalable, multicloud and cloud federation infrastructure (Pawar et al., 2015).

16) **Sensing-as-a-Service (S2aaS)** is a cloud-powered sensing service that is offered through mobile phones. S2aaS has enormous scope to serve under IoT paradigm and also highly useful in environmental monitoring, social networking, healthcare, transportation and several other domains, where sensing is an important part. S2aaS is highly energy-efficient service and supports several sensing applications through various smartphone platforms (Sheng et al., 2013).

17) **Sensor-as-a-Service (SenaaS)** is a cloud-powered service that is delivered for ubiquitous management of the remote sensors. However, SenaaS has no role in any type of data collection or data dissemination mechanism for the sensor data (Zaslavsky et al., 2013). SenaaS is another qualified candidate that also has huge opportunities to serve in IoT paradigm.

18) **Sensing and Actuation-as-a-Service (SAaaS)** is to develop a cloud of sensors and actuators and deliver it as a service for sensing and actuation process. The inclusion of sensors and actuators initiates the creation of new, value added, quality services that eventually leads to pervasive cloud computing (Distefano et al., August 2012). Similar to SenaaS, SAaaS also has wide utility in IoT paradigm.

19) **Sensor Event-as-a-Service (SEaaS)** is a cloud-supported service for message and alert notification. The service is enabled and triggered at the sensor events. It also grants access privileges to the users on sensor data and measurements. SEaaS imparts capabilities for generation, subscription, and retrieval of the message and alert notifications. SEaaS allows users the dynamic registration of the sensors, which is followed by subsequent service notifications (Dash et al., 2010; Rao et al., 2012). Also, the role of SEaaS in IoT paradigm is expectedly highly promising.

20) **Storage-as-a-Service (StaaS/SaaS)** is a cloud-based service to store the data in online storage space in cloud. StaaS/SaaS has robust cryptographic algorithms to address the user concerns about the data security and privacy. StaaS/SaaS also claims the lower computation cost, higher security and sensitivity based on data significance (Patel et al., 2012).

21) **Things-as-a-Service (ThiaaS)** allows the implementation of innovative and the value-added services in a cloud environment that is integrated with IoT paradigm. ThiaaS provides the mechanism to construct a cloud of things, where the multifarious resources are either aggregated or abstracted (Distefano et al., July 2012). Therefore, ThiaaS obviously is one of the most qualified and useful services in IoT evolution.

22) **Video Surveillance-as-a-Service (VSaaS)** is a cloud-enabled service for video surveillance and facilitates video recording, storage, remote viewing, and cyber threat and security management. For the on-premises installed surveillance devices, the VSaaS shifts the video processing, management and analysis in cloud environment unlike the conventional systems, where the computations are locally performed by the computing unit attached to the device itself (Prati et al., 2013), which add significant overheads that may dampen the performance.

6 Discussions on Emerging Services and Analytics

In order to obtain the valuable information from mammoth Big Data, it requires to be subjected through the robust and advanced analysis processes. The emerging services and analytics help unwrapping the important hidden patterns, uncertain correlations. Due to the semi-structured and unstructured complex nature, Big Data often does not fit well in traditional analytic techniques and thus requires comprehensive software frameworks that are fully equipped with advanced analytical technologies such as data mining, predictive and statistical analyses, etc. Additionally, the mainstream data analytics tools also have tightly coupled vigorous data visualization capabilities, which provide exceptional support even to the real-time data analytics. Over the years, the data analytics has been expanded to seamlessly integrate the visualization aspect and in data science, it is popularly known as visual analytics. The visual analytics offers the complete view of data in order to obtain value insights. The state-of-the-art data analytics tools are potentially innovative and powerful and are highly capable for multidimensional data visualization, which imparts a stronger perception of data landscape and extra intuitive understanding. Today, there are several software tools for visual analytics that are either open source or commercially available such as IBM’s InfoSphere and BigInsights (Keahey, 2013). These tools are developed with the emerging technologies and help advancing the human capabilities related to intrinsic pattern recognition.

As, the new data-related challenges are surfacing due to the evolution of IoT, the scientific communities are developing new services and analytics tools at the same pace to efficiently address them. Pachube (Haque, 2004) is believed to be one of the few providers, which begin the online data-related services, especially facilitates the attachment of sensor data to Web. Today, it delivers an IoT-enabled platform for cloud-based real-time data management. Nimbits (Nimbits Inc., 2015) is IoT-supported, cloud-powered, open-sourced, freely available social platform that assists in sensor data collection, storage, and sharing through cloud services. iDigi (Digi International Inc., 2015) is a rich PaaS framework, quipped with all the required tools & techniques for the secure, cost-effective, and scalable connectivity, integration and communication management of enterprise applications with remotely located sensing devices, independent of network and location. Talia (2012) agrees that the cloud-assisted infrastructure can effectively be used for Big Data storage and analytics. The author also discusses the diversity of data, its complexity and computation capacity for large data analytics. The growth of data also increases its complexity and consequently the concurrent processing also becomes overly complicated. In such situation, the use of cloud-enabled environment certainly becomes a necessity (Ji et al., 2012) as the traditional settings gradually succumb to the growing data stress, become infective, choked and eventually ceased. Dean and Ghemawat (2008) suggest MapReduce as one of the good framework to process Big Data as it enforces parallel computation in clusters under distributed environment. Bollier et al. (2010) discuss the merits of cluster computing and its potential to amicably address the data growth. Miller (2013) discusses the drawbacks of peer pressure of organizations for quick adaptation and implementation of upcoming technologies e.g. cloud computing to have reasonably balance between the storage and computation capacities. Hence, the role of traditional DBMS cannot be ignored in this evolving cloud environment as it ensure a risk free and smooth transition of complex application from its end to cloud-assisted environment. Kwon et al. (2014) discuss the merits and demerits of Big Data analytics. The authors are convinced that Big Data analytics is an innovative approach that has the potential to boost the performance of the related entity. However, adoption of such capability does not seem trivial for each business entity because of shallow understanding and experience in Big Data; the authors have proposed a model to understand the relevant issues in early Big Data adaption. Singh et al. (2014) use some of the components such as Hive and Mahout of Hadoop ecosystem and build a scalable quasi real-time intrusion detection system. The developed system is a test-bed for real-time P2P Botnet detection, which acts as a pre-processing engine for existing IDS/IPS. Schnase et al. (2014) describe the major Big Data challenges in climate science and show how cloud computing can address them through a generative approach, Climate Analytics-as-a-Service (CAaaS). CAaaS is a Climate Data Services API owned by NASA and authors of this paper claim to be the first to describe that. Tannahill and Jamshidi (2014) construct a bridge between System of Systems (SoS) and Data Analytics to develop reliable models for such systems. The data analytics is used to generate a model to forecast the produced photovoltaic energy to assist in the optimization of a micro grid SoS. Aluru and Simmhan (2013) serve as editors on a special issue that address the issues occurring in Big Data management and analytics. Hipgrave (2013) explores the important aspects of smarter fraud investigations -- smarter technology, improved data visualization and better internal communication and seeks the possibility to take advantage of Big Data analytics to detect fraud fast and share critical investigative information. Zhang et al. (2013) also believe in MapReduce like framework for parallel data processing in cloud. They discuss the migration of massive, dynamically-generated, geodispersed data into the cloud with timely and cost-minimizing uploading strategies. Demirkan and Delen (2013) present a conceptual framework for service-oriented decision support systems (DSS in cloud) that suggests to migrate the analytics and Big Data in cloud. The authors also furnish the definitions Data-as-a-Service; Information-as-a-Service; Analytics-as-a-Service. Pandey and Nepal (2013) serve as the editors on CCSA2012 event that invited the high quality scientific publications addressing the issues related to diversified aspects in cloud computing. Lee et al. (2012) discuss the concerns of incapability of single cloud in handling the Big Data services and suggest to address these issues by multi-clouds (cloud-of-cloud/ rain computing). Srirama et al. (2012) take advantage of MapReduce framework in solving scientific computing problems. For more complicated problems, an alternate to MapReduce, called Twister is considered by the authors and results are analyzed in details. Yan et al. (2013) aim to expand the data scalability of power iteration clustering (PIC) algorithm by implementing a parallel PIC. Various parallelization strategies and implementation details are explored to reduce the costs, incurred in computation and communication also considering the commodity computers. Schadt et al. (2011) explore some of the diverse cloud computing strategies, presently available in biology with the aim to address the issues, surfacing due to the emergence of Big Data. ThingSpeak (2014) is another an IoT-enabled open-sourced SaaS platform, with rich set of APIs for data storage and communication from sensing devices. Madria et al. (2014) consider geographical area and propose a platform - Sensor cloud. It is a cloud-powered framework to virtualize the wireless sensors based on the covered geographical area. Sensor cloud can accommodate the on-demand multi-user networks connection simultaneously over a large geographical area. In IoT age, Sensor cloud, a multi-user environment, is being considered as a potential substitute of resource-constrained physical traditional wireless sensors.

Each one of the cloud-based emerging services, described in section 5 is highly robust in the dedicated job execution for which it is designed and developed. CLAaaS is an effective service for IoT-enabled applications, where each device generates lots of data that can be transmitted from one device to another device. It also supports the multi-faceted analyses of big data, on demand storage of data and other services through the customized user interfaces. It is one of the most reliable data-oriented services that leads on easy tailoring the client's requirements. In cloud environment, DaaS is considered as the most effective service for swift storage and management of Big Data, generated from various kinds of connected things such as sensors, circuits, actuators, etc. This data is aggregated from multiple machines or vehicles and stored in the cloud or storage devices. The integrity of IoT data among the sensor-embedded, wireless-enabled things is maintained through the services (DIaaS) that must use the upper edges of highly secure cryptographic hashing algorithms. It ensures that the data is not changed during transmission. The mining operations on IoT data are supported for both small and large volume in cloud environment, therefore, are suitable for small scale as well as large scale clients. In cloud, the mining services (DMaaS) are especially required for those clients, which have large volume of data, but comparatively limited budget for data analysis. In practice, the nature of IoT data can vary from little to extraordinarily large. The security and privacy protection of the device generated Big Data require the essential security measures in place. The security threats between sensor-actuator and networks are an eavesdropper listening on data or commands that can reveal information about the operations of the infrastructure. A fake device in IoT network may inject fake measurements that can cause the failure occurrences, managed through FaaS; it can disrupt the control processes, resolved most effectively through IPMaaS and can also react inappropriately or dangerously. Also, it can be used to mask physical attacks and in between network and server. The maintenance of security services (SecuaaS/SaaS) in IoT is extremely hard, resource-exhaustive and high-priced; the sustenance of such services requires the expert resources. The sensing services (SaaS/SenaaS) in IoT support the data acquisition from the ubiquitous sensing systems, actuators or other devices that extract the system logs or operating on the data, gathered from other machines or vehicles and transmit wirelessly. The sensors or actuators in IoT exploit the sensing services (SaaS) through various handheld devices. In the cloud environment, such energy-efficient IoT services have the ability to support various sensing applications on different platforms. The commodity things in IoT are highly likely to communicate the message and alert notifications. The message and alert related services are supported through SEaaS. VSaaS outperforms the other cloud services of same nature when it comes to surveillance related services. It is a highly-ranked, trustworthy, robustly secured efficient service. In surveillance systems, the IoT-enabled objects/devices/things generate the vast amount of video data such as recording, remote viewing etc.; the cloud coordination for the device-generated data management though VSaaS delivers additional robustness to the comprehensive surveillance systems. Chang and Wills (2015) analyze the effective methodologies and metrics for fair performance comparison between cloud and non-cloud storage systems to for efficiency and performance improvements. Chang, Kuo and Ramachandran (2015) build a cloud framework-Cloud Computing Adoption Framework (CCAF) and to address the recent real-time security concerns for cloud data of petabytes range, CCAF is tailored to provide robust security to the clouded data. Also, discussed are the overview, rationale and components in the CCAF.

7 Impacts and Benefits to Businesses

This section illustrates some of the transformative and sustainable impacts and benefits of Big Data, IoT, cloud-based the emerging services and analytics to the business domain. Over the last few years, the advancements in data science has transformed the business domains. The availability of multidimensional, heterogeneous and voluminous datasets and functionally-rich data engineering and analytics models have greatly impacted the businesses and the robust analyses of the data through various dimensions have delivered uncountable benefits that have enormously contributed in sustainable growth of the businesses. As, the services and analytics are capable to illuminate the complex relationships of the variables of the data and hidden patterns, the business entities now take the best advantages of emerging services and analytics in uncovering the dubious market trends, variations in customer preferences, etc. The findings through analytics can lead to several efficacious improvements to the present state of the entities in a related domain. For example, for a business domain, the unraveled information can help in ameliorating the marketing strategies, enhancing revenue generation, delivering more effective customer related services, ensuring upgraded operations etc. The use of the recommendation systems is widely and popularly witnessed in almost of kinds of businesses to improve their sale, which intelligently and dynamically analyze the previous purchasing trends of the buyer and consequently recommend new products to them on their return. Therefore, the emerging services and analytics have impacted the businesses in effective ways for better informed decision making process.

The footprints of the impacts and benefits of emerging IoT in businesses are not yet fully expanded, but early traces have begun visible. The businesses believe to have innovative impacts, especially organizational and institutional as the aura of IoT grows and transforms the traditional business performance and procedures. The IoT-led huge data generation as a result of normal daily operations or chores is seemingly to offer enormous opportunities to draw benefits to the businesses. However, the generation of invaluable or unnecessary data, may be in small quantities, is susceptible to adversely impact the businesses instead as such data is more vulnerable to misuse that may proceed to invalid or untrue conclusions. Some of the obvious benefits, the IoT is expected to deliver to businesses and also to communities are energy conservation, reduced costs and public safety. However, the data privacy and protection in IoT will have critical influence from the public behavior and opinions. Also, the data privacy and protection will be impacted by the extent the behavior-related private information of people are allowed to be public, where certain behavior events trigger the harvesting and trading of the information. As, IoT is increasingly integrating the technological systems at large-scale, in near future, the businesses may be greatly benefitted with the IoT-enabled automation that will favorably impact the business quality, reliability, and sustainability.

The inclusion of cloud-supported computing environment has witnessed tangible impacts and quantifiable improvements in business domain. The SaaS model helps the businesses to maintain the most up-to-date version of their software applications, required for successful run of the business, and to make is globally available with zero down-time. The improved features as new enhancements in typically frequently new releases are made available for public use in no time; this leads to highly positive impact on the businesses and helps enhance the business productivity and sustainability. The highly affordable cloud-environment, equipped with the rich set of extremely secured robust services has inspired the almost all the businesses to partially or fully migrate their large, expansive, exceptionally protected and secured data centers. This in its entirety helps reduce significantly (a substantial part of business budget) the IT-related operational cost of the businesses and upwardly impacts them with improved IT capabilities. The cloud-housed applications are good candidates for collaboration that through shared storage, easily share the dispersed but relevant information in real time; the subsequent analyses of such information may help improve the product development and customer service; this also will lead to reduction in time-to-market. The businesses take best advantages of the flexible nature of cloud computing technology, where, on demand, the additional capacity to the provisioned resource can be quickly provided during a sales promotion to successfully accommodate the sudden increase in customer traffic and to avoid any slowness in response time, hence to avoid losing sales; once, the promotion is over, the previous capacity is requested back and thus operate back on the reduced cost after comparatively a short-lived spike. The worldwide cloud adaptation in businesses has substantially reduced the number of energy-hungry data centers and is aiding the energy efficient operations. In sum, the cloud environment and the cloud-based emerging services are enforcing the reduction of the carbon footprints, promoting the healthy and green environment and encouraging the businesses for enhancing the green credentials (West and Goldenberg, 2012).

8 Conclusions and Future Work

This work provides a comprehensive illustration about the cloud-based emerging service and analytics. The selection of the services of interests is majorly influenced by their utility and applicability in IoT paradigm. Additionally, other important and useful emerging services are also briefly explained, especially for the business domain. The management and mining of large volume of data amassed, especially from the sensing systems are posing sturdy challenges to the traditional techniques. This is where, the quest for new emerging services and functionally-rich multifarious analytics begins; today, the concept of cloud computing has emerged as the most sought destination that promises to effectively address the data triggered challenges. In this paper, we further understand the broader concept of cloud environment that imbibes the emerging services and analytics also and has revolutionized the perspective of management and sharing of IT resources and services. The applications with complex data-intensive computations are the best candidates to qualify for cloud computing advantages. The next generation emerging service developments are bridging the gap and helping the cloud computing to gradually accommodate the IoT challenges completely and providing the abundant analytics tools to the end users.

The core contribution of this study was to explore the cloud-based emerging services that helps in comprehensive data analytics for even technical naïve end users such as stakeholder, director, manager, etc. We briefly overviewed the concept of cloud computing and explored some emerging services, may be useful in IoT. It was discerned that the number of data management systems had grown swiftly in last few years and was still expanding. Each data model claimed to outperform others with its unique storage technology and computing mechanism. For a cloud-interested user, to find the most suitable cloud-enabled model, it became too difficult to examine the underlying technology through the big pool of available models. Therefore, we presented a novel classification, called CNNC {Clouda, NNClouda}; the basis of the classification was the scientific name of the models and intended to harness their intuitiveness to better assist the users. Hypotheses were used to validate the proposed classification and some of the available models of each class were investigated to test the correctness. The investigation revealed, a cloud-powered model was correctly classified as either Clouda or NNClouda, but certainly fallen under CNNC classification. However, in one instance, interestingly a model (LightCloud) was found qualified for Clouda subclass, but was not cloud-powered at least yet. This basis helped inferred that Clouda class not necessarily had all the models as cloud-supported. The CNNC classification was further strengthen through some related case studies. Additionally, being cognizant of IoT scope, some important emerging services and analytics were also explored. Future work includes the further expansion of the discussion on the emerging services and analytics from the perspective of integration of the emerging technologies in various domains.

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