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A prototype of Artificial Intelligent Application Model on IoT Platform

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Abstract: In this study, we propose a prototype an effective implementation for internet of things used for monitoring tubiquitous sensing system.The description about the integrated network architecture and the interconnecting mechanisms for the reliable measurementof parameters by smart sensors and transmission of data via internet is being presented. The longitudinal learning system wasable to provide a self-control mechanism for better operation ofthe devices in monitoring stage. The Internet of Things (IoT) gets real. Already today, there are more connected devices than humans. In contrary, there is hardly any systematic research available that evaluates the capabilities of existing IoT platforms. This study contributes to the understanding of the current IoT platform landscape by reviewing six selected commercial IoT platforms and by inducing an architectural model which depicts the main building blocks of an IoT platform in a comprehensive way. The framework of the monitoring system is based on a combination of pervasive distributed sensing units, information system for data aggregation and reasoning and context awareness.

Key words: IoT (Internet of Things), artificial intelligence, deep learning, knowledge system, platform

INTRODUCTION

Recent neuro science findings have provided insight into the principles governing information. Representation in the mammal brain, leading to ideas for designing systems that represent information.

One of the key findings has been that the neocortex which is associated with many cognitive abilities, does not explicitly pre-process sensory signals but rather allows them to propagate through a complex hierarchy of modules that, over time, learn to represent observations based on the regularities they exhibit. This discovery motivated the emergence of the subfield of deep machine learning which focuses on computational models for information representation that exhibit similar characteristics to that of the neocortex (Kelly *et al.*, 2013).

In addition to the spatial dimensionality of real-life data, the temporal component also plays a key role. One of the key findings has been thatthe neocortex which is associated with many cognitive abilities does not explicitlypre-process sensory signals but rather allows them to propagate through acomplex hierarchy of modules that over time, learn to represent observations based on the regularities they exhibit. This discovery motivated the emergence of the subfield of deep machine learning which focuses on computational models for information representation that exhibit similar characteristics to that of the neocortex (Ras and Dardzinska, 2004).

To that end modeling the temporal component of the observations plays a critical role in effective information representation. Capturing spatiotemporal dependencies, based on regularities in the observations is therefore, viewed as a fundamental goal for deep learning systems. Assuming robust deep learning is achieved it would be possible to train such a hierarchical network on a large set of observations and later extract signals from this network to a relatively simple classification engine for the purpose of robust pattern recognition. Robustness here refers to the ability to exhibit classification invariance to a diverse range of transformations and distortions including noise, scale, rotation, various lighting conditions, displacement, etc. (Arel *et al.*, 2010).

This study propose a prototype model of the mainn stream deep learning approaches and research directions proposed overthe past decade. It is important to emphasize that each approach has strengths and weaknesses, depending on the application and context in which it is being used. Thus, this study presents a summary on the current state of the deep machine learning field and some perspective into how it may evolve. Convolutional neural networks and deep belief Networks are focused on primarily because they are well established in the deep learning field and show promise for future work.

Literature review

Internet of Things (IoT): They focus on logistics where goods need to be uniquely identifiable and trackable in

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order to build a self-organizing network where goods find their way like data packets do in the ordinary internet another approach to the IoT stems from telemetry. Here, sensor data from remote places has to be transferred to a central site. With the advent of mobile phones and cellular networks, telemetry evolved to machine-to-machine communications. Typical applications are fleet management and asset tracking. Here, everyday objects and even the environment get network connectivity (Kohelr *et al*., 2014).

The industry, especially network providers, often uses the term M2M and IoT interchangeably. In contrast, most of today's M2M applications are heavy weight custom solutions that are in no way based on standards and interoperability. Notably, the term M2M is usually business-centered whereas the vision of ubiquitous computing is human-centered. Furthermore, in typical M2M scenarios, the computation and intelligence is centered at one specific location whereas ubiquitous computing is concerned with distributive computing where computational tasks can be distributed among the network.

Related to ubiquitous computing, the research field of Wireless Sensor Networks (WSN) and Wireless Personal Area Networks (WPAN) emerged in the mid-1990s. Both build self-organizing networks of smart objects which can interact with the physical world around them. Today's typical WSN/WPAN scenarios involve proprietary wireless protocols like ZigBee and Z-Wave where gateways are needed to translate between proprietary and IP networks. These gateways often need application specific programming and are not interchangeable. In addition, there are small WPAN solutions using bluetooth where the smartphone typically acts as a gateway or mediator.

MATERIALS AND METHODS

IoT platforms: IoT platforms provide a comprehensive set of generic, i.e., application independent IS functionalities which can be leveraged to build IoT applications. In the context of our work, prior research in the domain of IoT platforms has identified key IoT building blocks on the basis of a deductive as well as inductive manner. Castro is one of the very few studys which conduct an analysis of M2M platforms based on an inductive approach. Moreover, while it is indeed hard to select platforms on a set of objective criteria in a transparent way, they just select platforms for their analysis without providing any argumentation. To the best of our knowledge there is no research available deriving an overall architecture of functional building blocks on the basis of existing platforms (Kohler *et al*., 2014).

Several other approaches derive functional IoT platform building blocks on the basis of a deductive process. Atzori for example, provide an overview on IoT developments. As one part of their overview, they describe major building blocks of IoT solutions. While they do not depict a comprehensive survey of each building block they thrive to convey the role each building block will likely play in the IoT. Overall, they identify three major IoT building blocks: technology, middleware and applications.

Atzori point out the importance of service oriented architectures and decompose middleware into the four building blocks service composition, service management, object abstraction as well as trust, privacy and security management. As a second example, Lempert provide a very detailed architecture based on an ESB architecture. However, the overall development process of the artifact remains largely unclear. They hardly argue why each of the building blocks is needed and how they deduced the model.

Deep learning: To that end, modeling the temporal component of the observations plays a critical role in effective information representation. Capturing spatiotemporal dependencies based onregularities in the observations is therefore viewed as a fundamental goal fordeep learning systems. Assuming robust deep learning is achieved it would be possible to trainsuch a hierarchical network on a large setof observations and later extract signals from this network to a relatively simple classification engine for the purpose ofrobust pattern recognition. Robustness here refers to the ability to exhibit classification invariance to a diverse range of transformations and distortions including noise, scale, rotation, various lighting conditions, displacement, etc.

This provides an overview ofthe mainstream deep learning approachesand research directions proposed overthe past decade. It is important to emphasize that each approach has strengths and weaknesses, depending onthe application and context in which itis being used. Thus, this study presents asummary on the current state of the deep machine learning field and some perspective into how it may evolve. Convolutional Neural Networks (CNNs) and Deep Belief Networks (DBNs) (and their respective variations) are focused on primarily because they are well established in the deep learning field. Nodes independently characterize patterns through the use of abelief state construct which is incrementally updated as the hierarchy is presented with data.

This rule is comprised of two constructs: one representing how likely system states are for segments of the observation, P(observation|state) and another representing how likely state to state transitions are given feedback fromabove, P (subsequent|state, feedback). The first construct is unsupervised anddriven purely by observations while the second, modulating the first, embeds the dynamics in the pattern observations.

IoT platform model

Derivation of the model: The induction of the consolidated model is based on the construction of reference models. In essence, functional building blocks describing similar functionality are consolidated in the induced model. We distinguish three different abstraction layers in the model.

First of all, the analyzed platforms greatly vary in their general scope. Some platforms offer capabilities to develop and run applications on end user devices, i.e., general-purpose computers like PCs or smartphones. Others provide functionality to develop and run embedded applications on “things”. Finally, the platforms provide functionally to centrally coordinate and process execution. In M2M scenarios most often M2M middleware solutions and enterprise applications take over the central coordination and processing role. In consumer oriented IoT scenarios like smart home a gateway might act as the central coordination instance (Kohler *et al.*, 2014).

The functionality provided by the platforms can further be classified into two general functionality types. There are libraries and code frameworks which can be leveraged for application development and execution. We refer to this type of functionality as core functionality. Furthermore, there are tools for development as well as life cycle management, i.e., managing the platform at runtime. As these tools regularly “span across”, the core function alities provided by the platform, we refer to this type of functionality as cross functionality. The last abstraction layer comprises more fine grained functionality offered by the platforms. The elements of this layer are directly induced from the analyzed platforms. This process make transparent by depicting which platform offers which functionality.

Description of the model: Most of the previously depicted platforms provide functionally to centrally coordinate and process execution. Six functional core building blocks can be distinguished in this context. Data management capabilities include machine data collection and storage as well as data integration services. Some platforms offer capabilities to store and analyze vast amount of machine data. In the context of trends like “Big Data” these capabilities are promoted heavily. Other platforms focus on integrating data from different sources on the basis of simple data integration (“mashup”) environments. They promise to integrate structured as well as unstructured data from social sources.

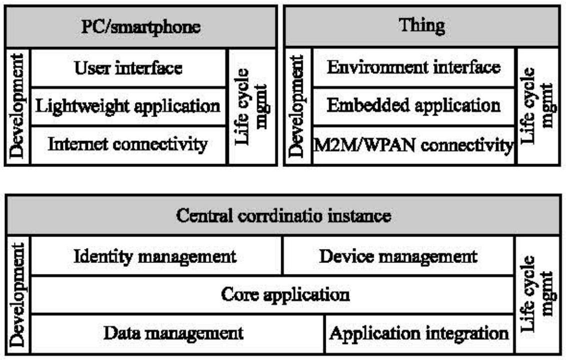

Fig. 1: Building blocks of an IoT architecture

Identity management allows administrating user identities as well as resources, e.g., devices or application services across the platform. Granting and revoking access to resources as well as providing authentication services are fundamental capabilities for executing security policies. Furthermore, monitoring and analyzing access logs are the basis for auditing and security analysis.

Device management provides capabilities to provision, activate and manage devices. This covers functionalities such as remote access, configuration, administration, software management, device monitoring and troubleshooting. Furthermore, some platforms support the automated delivery of firmware and configuration updates during run-time.

Some platforms provide functionality to rapidly build frontend applications. They offer tools to create HTML5-based user interfaces and lightweight frontend applications, e.g., on the basis of dashboards. Standard internet connectivity is leveraged to connect these frontend applications to the core application running on a central instance refer to Fig. 1.

RESULTS AND DISCUSSION

Prototype

System architecture: The overall architecture of our system is shown in Fig. 2. On the behalf of context consumer Enforcement module, context agent module collects, integrates context and ontology from context middleware like Gaia. On-demand method can be used by context agent wanting to obtain context and ontology immediately upon query request. Subscription method can be used by context agent wanting to request to be notified whenever relevant contexts are updated newly (Bo-Young, 2011).

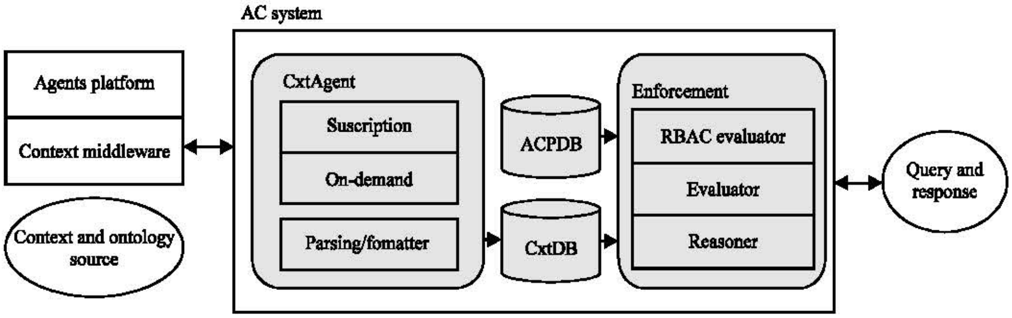

Fig. 2: Prototype of AC system architecture

We request (response) the SAML message before issuing the assertion by SAML authority. Hence, we reduced the assertion creation time than the existing algorithms. And yet, SAML message can certificate message protocol because is included the digital signature and trust information. Also, UA decreases the assertion verification time too because delegate the privilege to task agent before issuing the assertion. This means that task agent is confirmed only once authentication to SAML authority.

Implement algorithm: The authorization involving static context components is explicitly specified by the security administrator. The authorization involving derived context is automatically generated with inference rules on query execution time. So, both could be conflict in some case. When conflict occurs, we suggest the negative authorization takes precedence.

Algorithm 1 (Enforcement algorithm):

```
enforcement(s,p,cq) {
// In: subject s, permission p,
query context collected dynamically cq
// Out: yes/no (permit/prohibit)
IF basic-authorization au is not matched THEN
RETURN no;
(2) IF context constraint cq is not matched THEN RETURN no;
(3) CQ:= Find a set of concepts relevant to cq;
(4) CP:= Find a set of concepts relevant to au <s,p>;
(5) FOR each predicate q in CQ
(6) FOR each p in CP
(7) IF q is a element of CCH(p) THEN RETURN yes;
(8) RETURN no;}
```

Algorithm 2 (Verification algorithm): Algorithm 2 is the assertion verification algorithm. TA encrypts the assertion as ServiceAgent's public key and send. SA decrypts the assertion as SA's private key and confirms digital signature. If digital signature is not valid, SA sends the reject message to TA. And SA checks whether SA verifies the three statements valid or not.

Algorithm 2 (Verification algorithm):

```
Algorithm: Assertion verification algorithm
INPUT: SAML Assertion
OUTPUT: Decision (Accept, Reject, N/A)
Each Service Provider (SP) verify Assertion from Task Agent (TA)
SP secrypt Assertion by $Pk_{sp}$.
If (Signature is not valid) Then
    Return Reject
  else
    If (AuthorizationDecisionstatement is valid) Then
  else
    Return Reject
      If (Attribute statment is valid) Then
        AuthenticationStatement Verification
      else
        Return Reject
        If (AttributeStatment is valid) Then
          Return Accept
        else
          Return Reject
```

CONCLUSION

In this study, we propose a prototype model and multilayered data cloud platform based on cloud computing and IoT technologies. We also discuss how cloud services could be developed to make the data clouds useful. IoT-based data clouds are expected to be the backbone of future ITSs with the ultimate goal of making driving saferand more enjoyable.

However, research on integrating IoT withthe data clouds is still in its infancy and existing studyon this topic is highly insufficient. A number of challenges such as security, privacy, scalability, reliability, quality of service and lack of global standards still exist. Due to the complexity involved in implementing data clouds and integrating various devices and systems with application clouds (He *et al*., 2014) a systematic approach and collaboration among academia, the automobile companies, law enforcement, government authorities, standardization groups and cloud service providers are needed to address these challenges. Though with many challenges, IoT and cloud computing provide tremendous opportunities for technology innovation in the any industry and will serve as enabling infrastructures for developing some data clouds.

REFERENCES

Arel, I., D.C. Rose and T.P. Karnowski, 2010. Deep machine learning-a new frontier in artificial intelligence research (research frontier). IEEE. Comput. Intell. Mag., 5: 13-18.

He W., G. Yan and D.L. Xu, 2014. Developing vehicular data cloud services in the IoT environment. IEEE. Trans. Ind. Inf., 10: 1587-1595.

Kelly, S.D.T., N.K. Suryadevara and S.C. Mukhopadhyay, 2013. Towards the implementation of IoT for environmental condition monitoring in homes. IEEE. Sens. J., 13: 3846-3853.

Kohler, M., D. Worner and F. Wortmann, 2014. Platforms for the internet of things-an analysis of existing solutions. Proceedings of the 5th International Conference on Bosch Systems and Software Engineering, October 17, 2014, University of St. Gallen, Gallen, Switzerland, pp: 1-10.

Ras, Z.W. and A. Dardzinska, 2004. Ontology-based distributed autonomous knowledge systems. Inf. Syst., 29: 47-58.