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ENERGY AND RESOURCE USAGE-AWARE BUILDINGS VIA COGNITIVE INTERNET OF THINGS AGENTS

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Abstract *There are several ways to improve the economic sustainability of buildings, such as through embedded systems, or automation, through sensors and actuators. In both cases, human supervision is omnipresent. On the other hand, the emerging Internet of Things (IoT) is the inception of a new era where the devices (computers, cell phones, embedded machines, sensors and actuators etc.) are connected to each other through the internet, and it can be a practical platform for further automation of energy management. In this work we show how cognitive software agents, enabled with machine learning techniques, can support intelligent behaviour for the management of a building's infrastructure. Indeed, cognitive models can reduce human efforts in tasks like managing energy consumption, energy efficiency analysis for potential of energy saving, energy-aware networking and power management, freeing humans' attention for more critical tasks or more abstract level monitoring of the building.*

Intelligent management of buildings requires the discovery of energy or resource consumption patterns; these must be gleaned from the data generated by the large group of sensors in the building. Such pattern identification and characterisation is a challenging task, both because of the very-high dimensionality of data (coming from many sensors) and of the real-time character of the input data stream. Manual processing is patently unpractical, but a Machine Learning approach seems appropriate. In this work we use the Regulated Activation Networks (RANs) cognitive model to discover and characterise such patterns thus enabling the development of Cognitive IoT-based energy management solutions.

1. INTRODUCTION

The Internet of Things (IoT) paradigm enables the development of a vast range of sensor-based applications, allowing for the implementation of realities such as smart cities, smart transportation, buildings etc. These are achievable via optimal device utilisation, attaining computational efficiency, reduction in energy consumption, and storage of data [1, 2, 3, 4]. Specifically, IoT technologies can be very helpful for managing buildings, primarily, in two aspects; first, significant reduction in energy consumption; and secondly, improving humans' satisfaction [5]. IoT intelligent devices also enable monitoring (like alarms, vigilance, etc.) in a building. Several challenges [5, 6], related to data, are identified and require attention due to rapid increase in number of devices in IoT [7]. The authors of [3] proposed a cognitive framework to for massive data analysis. Importance of cognitive modelling is also seen in the work [8] where knowledge is extracted from raw traffic data. Moreover, the adoption of IoT devices throughout buildings in a city will mean a very large number of devices (like sensors, actuators, cameras, and so on.), producing a large amount of data, Dark Data [9]. One of the hurdles in comprehending the complexity of such data is its high-dimensionality [3]. In this article, we address the barrier of high-dimensionality of data by learning abstract concepts/ features/patterns in the data and forming a deep representation of it. We learn the abstract concepts through Regulated Activation Networks (RANs) [10,18], a computational cognitive model, that dynamically learns and creates a deep representation of categories/patterns found in the input data. The article is organised as follows: first, we lay down the background for IoT, and Cognitive models and their significance in CIoT for Buildings; then, we describe the cognitive model RANs; further, we demonstrate how RANs are used to identify patterns in the input data; finally, we end the paper with concluding remarks and future work directions.

2.BACKGROUND

This section highlights the concept of IoT and its implication in smart buildings. We also provide information about cognitive models, their capability of learning from data, and how they can contribute for the realisation of smart buildings.

The main objective of having a smart building is to have efficient energy consumption, reduced maintenance cost, a prompt monitoring for safety, and improved security. A variety of sensors are available to perform building monitoring [11], as shown in Figure 1. These sensors collect data for monitoring and transmit it through a network (wired or wireless) — one such network has been demonstrated in [12] with Wireless Sensor Networks (WSNs) [13]; WSNs are playing a vital role in IoT [14].

Figure 1. Sensors for Building monitoring

The IoT paradigm relies on a universe of objects (like physical devices, vehicles, buildings, etc.) having integrated software, electronics, sensors and actuators, and internet connectivity, integrated into one congruent system. These objects observe, collect, and exchange data. In buildings, IoT devices enable intelligent behaviours by monitoring and helping in controlling various electrical and electronic system remotely. In the IoT, the connected devices share their observations, but, as argued in [3], being connected is not enough to fully reap the potential of the IoT: participating devices must also be able to comprehend the dynamics of the surrounding environment.

Computational cognitive models/architectures [15] have contributed significantly in Artificial Intelligence (AI) tasks by simulating human-like comprehension. The computational cognitive model/architectures can be symbolic (ACT-R [16]), Sub-symbolic (Neural Networks [17]), and Hybrid. These models/architectures have been effectively used in several domains like recognition, regression, classification, and prediction. The data produced by IoT infrastructure can be used by a learning cognitive model to enable the development of smart energy management solutions. We now present the application of the Regulated Activation Networks [10,18] cognitive model in this Cognitive IoT domain for efficient energy management in buildings.

3.PROPOSED METHODOLOGY

The Regulated Activation Networks (RANs) [10,18] is a connectionist computational cognitive model. For the RANs, an input datum is a point in a n-dimensional feature-space , as inspired by the theory of Conceptual Spaces [19]. The model is connectionist in nature with a dynamic topology, i.e., the network dynamically grows higher layers wherein nodes represent the categories discovered in lower layers. A RAN not only learns and creates a deep representation of concepts/categories identified in a given data-set, but also it learns the association among various level of abstraction within the model. The model works based upon 3 essential operations:

• **Concept Identification:** is the process of identifying categories within the input data – the RANs do so by resorting to user-parameterized clustering algorithms, producing cluster centroids as the newly identified concepts.

• **Concept Creation** is the process of creating a new higher layer in the network, with one new node per concept identified in the layer immediately below. The weights connecting each higher layer node to the lower layer nodes represent the coordinates of the higher layer centroid-node along the lower layer feature nodes.

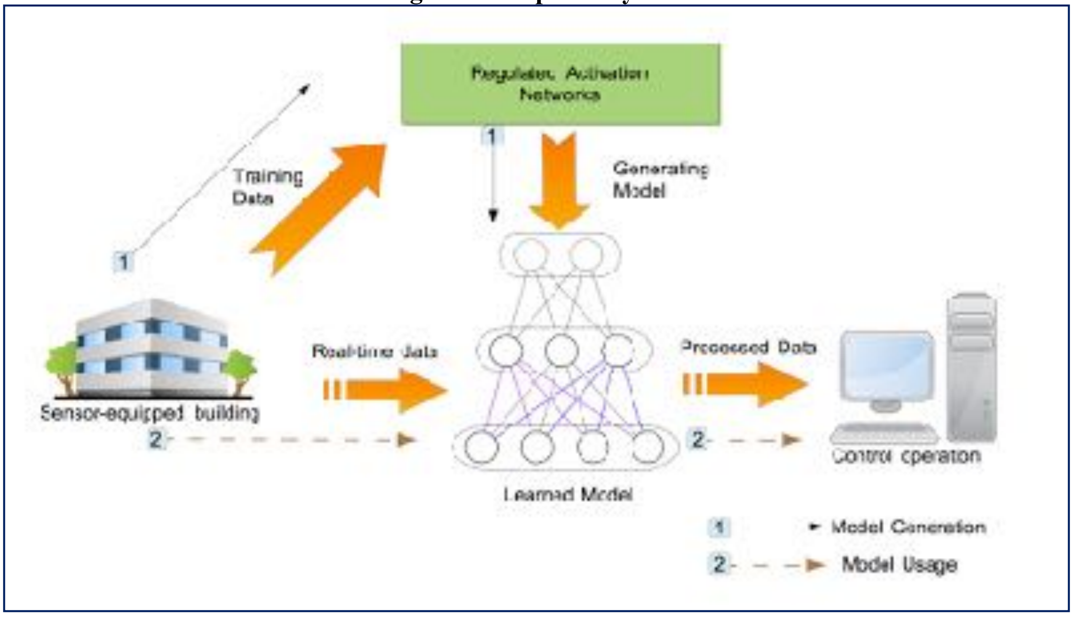
• **Upwards Activation Propagation** is the process of propagating the activation upward, from a lower layer to the newly created layer, by a Radial Basis Function between the lower-layer injected input data and the higher-layer centroid. It produces a re-representation of input data in the higher-layer centroid-space allowing for further concept identification to take place from this level upwards.

All the above-mentioned operations are repeated until the dimension of the top-most layer is stable. Once these operations concluded we obtain a model, a deep representation of the knowledge. The RANs also provide a fourth, generative, Geometric Back-propagation algorithm, to obtain an input-data-level representation of higher layer concepts.

The model obtained through a RAN, usually, reduces the dimension of the input data in the learned layers. The activation of a node in a new layer not only shows a new representation of the input-data, but also give a valuable information about the number of abstract categories and to which category does a particular datum-pattern belong. E.g., consider the model shown in Figure 2, with 2-nodes in the top-most layer: it depicts that two categories were identified at the intermediate layer below it; an activation pattern [0.85, 0.15] at the top-most layer corresponds to a 85% (15%) certainty that the input datum belongs to the category represented by the left (right) in the top-most layer.

Figure 2 shows how the RANs can be used to learn from data produced by sensors in a building: the data, produced by sensors, is provided to a RAN, which learns a deep representation of the data via its concept-identification, concept-creation, and upward-activation-propagation algorithms, iteratively. Once the model is obtained, it can then be used for monitoring and control operations.

Figure 2. Proposed System



4. SYSTEM DEMONSTRATION

In this section we perform the simulation RANs model with Gas sensors for home activity monitoring Data Set [20]. The data has 10-attributes, collecting sensor-resistance data from 10-sensors (8-TGS2XXX figaro, 1-temperature, and 1-humidity). The sensors were assembled to observe presence of wine, or banana, or none with respect to background activity.

Experimental Setup

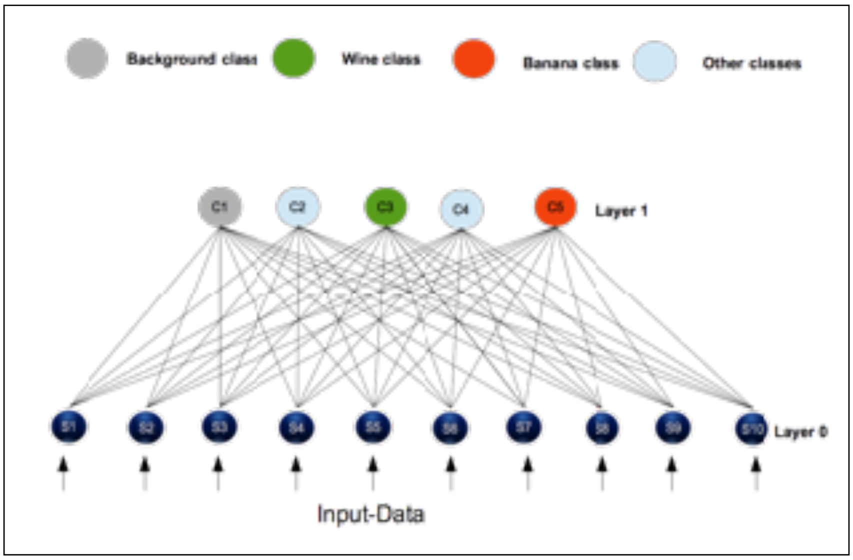
We extracted 15000 instances from the original data-set with 5000 samples from background (Category-1), 5000 from Wine (Category-2), and 5000 from Banana (Category-3) for our simulation. The RAN was initially configured to learn 3-categories in a supervised concept-identification task using the K-Means clustering algorithm — the network is configured to dynamically grow 1-layer with three nodes representing the categories. However, considering K=3, despite it being the real number of classes in the data and producing the smallest average error (cf. Table 1 below), caused the learnt model to fail to be discriminative in the sense that input instances of the class 'Banana' and of 'Wine' were activating the same cluster-node in Layer-1 when activation was propagated upwards. I.e., the 3 newly created nodes corresponded, respectively, to Background, Wine OR Banana, Outliers, instead of the intended Background, Wine, Banana. This pointed to the need for K > 3, which necessarily implied that, at least, some of the Background, Wine and Banana classes had to be represented by more than one node. We repeated the experiment with K=4, 5, …, 9 with Average Error results reported in Table 1. On the one hand, we wish to minimise the Average Error, but on the other we also want to minimise K (the top layer size) in order to avoid over-fitting; hence our aim was to find the minimum of AvgError*LayerSize. K=5 produced such minimum (cf. Table 1).

Table 1: Average error for K-nodes in Layer-1

Layer-size	Avg-Error	Layer-size * Avg-Error
3	14.41%	0.4323
4	32.67%	1.3068
5	***19.87%***	***0.9965***
6	19.87%	1.1922
7	19.87%	1.3909
8	28.46%	2.2768
9	28.94%	2.6046

Figure 3 shows the model generated by the input data with K=5. Each node in Layer-0 represents the attributes of the input data (normalised to fall inside the [0,1] interval). The data is first subjected to concept-identification through K-Means to identify 5-clusters. Then, 5 new nodes are created at Layer-1 through the concept-creation process, and the geometric associations between the Layer-1 nodes and Layer-0 nodes are learned and encoded in the inter-layer weights.

Figure 3. Model Generated By RANs



5.RESULTS AND DISCUSSION

As shown in Figure 3, the 10-dimensional input data are projected into a 5-dimensional class-space. Having learned the model, we propagated the input data to Layer-1 via the upwards-activation-propagation mechanism. Upon propagating data upward from input-layer (Layer-0) to layer-1, it is observed that the Background-class is identified as class C1 with 0%-error, whereas the Wine and Banana classes are identified as class C3 and C5, having 28.36% and 31.26% error percentage respectively. The overall misclassification was 19.87% in the data provided.
All the observations are summarised in Table 2 where the Data column represents the three categories (Background, Wine, and Banana), column Input Size contains the size of input-data being propagated, and the columns C1, C2,.., C5 represent the count of highest activations accounted at each nodes in Layer-1.

Table 2 shows the confusion matrix between the Categories known to be present in the data (Category-1,-2,-3) and the classes C1-C5 corresponding to cluster centroids materialised as nodes in Layer 1 of the learnt RAN model. The Error column corresponds to the percentage of input data instances that were classified under any of the C1-C5 classes not corresponding to the Cx class with the highest number of attributed input instances.

Table 2: Observations

Data	Input Size	C1	C2	C3	C4	C5	Error
Category-1	5000	5000	0	0	0	0	0%
Catrgory-2	5000	0	1405	3582	13	0	28.36%
Category-3	5000	0	0	1	1561	3437	31.26%
Total error	15000	5000	*1405*	3583	*1574*	3437	19.87%

In this Table 2 we can observe that the C2 node was attributed a significant percentage (28,1%) of the input data samples that, according to the RAN model, should belong to C3 — and the same happens with C4 (31,22%) and C5 regarding Category-3. This hints that Category-2 cannot be aptly represented by the single cluster C3, but only by a combination of clusters, e.g., C2 and C3.
However, performing a correlation analysis (cf. Table 3) between the activation values at C1 through C5 we see that there are unexpected high correlations, e.g., between C3 and C5. This points to the need of K>5 in order to improve the model's discriminance.

Table 3: Activation correlation matrix

	C1	C2	C3	C4	C5
C1	-	0.72	0.86	0.84	0.84
C2	0.72	-	0.72	0.84	0.74
C3	0.86	0.72	-	0.84	0.92
C4	0.84	0.84	0.84	-	0.86
C5	0.84	0.74	0.92	0.86	-

Indeed, performing a correlation analysis (cf. Table 3) between the activation values at C1 through C5 we see that C2 and C3 are highly positively correlated, as well as C4 and C5 which supports the hypothesis of a need for a way to combine these atomic clusters into larger unified classes.

Since activations at each Cx node are calculated via a Radial Basis Function, we can think of each Cx as the centroid of a hyper-spherical region of the feature space, where the RBF takes the distance between that centroid and the lower-layer input datum point. With this geometric interpretation in mind, each of these Cx regions has a convex shape. However, there is no guarantee whatsoever that the Categories in the input data have a convex shape in the feature space which further points to the need of a geometric method to merge the atomic hyper-spheres into larger non-convex regions that better fit the categories present in the data.

5. CONCLUSIONS AND FUTHER WORK

The IoT is expected to encompass beyond 20-billion devices, and all will produce a huge amount of highly-dimensional data. This high dimension introduces unavoidable challenges, like visualisation, consequently limiting the human capabilities in monitoring, e.g., smart buildings. In this work we show how the Regulated Activation Networks model can be used to implement cognitive systems fed by IoT devices, thereby taking another step forward towards the realisation of the Cognitive IoT vision. With this approach we are not only able to reduce the dimensionality of the data being produced by the IoT devices, but also to learn the underlying categories within the data and build a model for further usage.

Moreover, the experiments with the dataset at hand have pointed out to the need for further development of the theoretical RAN model towards endowing it with the ability to join atomic clusters into larger non-convex classes, and we focus on this direction for future work.

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