A Deep Incremental Boltzmann Machine for Modeling Context in Robots

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Abstract— Context is an essential capability for robots that are to be adaptive as possible in challenging environments. Although there are many context modeling efforts, they assume a fixed structure and number of contexts. In this paper, we propose an incremental deep model that extends Restricted Boltzmann Machines. Our model gets one scene at a time, and gradually extends the contextual model when necessary, either by adding a new context or a new context layer to form a hierarchy. We show on a scene classification benchmark that our method converges to a good estimate of the contexts of the scenes, and performs better or on-par on several tasks compared to other incremental models or non-incremental models.

I. INTRODUCTION

Context, which can be defined as “the totality of the information characterising the situation of a cognitive system; e.g., it can include objects, persons, places, and temporally extended information related to ongoing tasks, but also information not directly related to these tasks.” — [1], is essential for many critical cognitive capabilities such as perception, reasoning, communication and action [2], [3]. Context helps these processes in resolving disambiguities, rectifying mis-predictions, filtering irrelevant details, and adapting planning.

It is known that contexts are hierarchical structures [4] such that we can think of sub-contexts of contexts. E.g., in a kitchen context, one can talk about the dishwasher context or making breakfast context that contain sub-groups of relevant objects and actions related to the kitchen context.

Robots, which are expected to share the same complex environments that we live in, should depend on context like we do. A robot should adapt its routine tasks, e.g., when there are children around, when it is carrying a hot drink, or when everyone is at sleep. To be able to accomplish that, a robot should be able to learn new contexts and change its behavior according to the current context.

Learning contexts should take an incremental approach since one cannot enumerate all spatial, temporal and social configurations (situations) that can be taken as contexts. Therefore, with every experience, looking at certain signals coming from the environment or the robot, the robot should be able to update its context model.

In this work, we take an incremental approach to modeling context in robots, as shown in Figure 1. Although there have been many studies in incremental topic/context modeling in linguistics [5] and robotics [6], [7], they are not hierarchical. There are promising hierarchical topic modeling efforts [8], [9], which however either assume a fixed depth structure or availability of all data at the model construction phase. Our approach, on the other hand, makes no assumption on the depth or the availability of the training data, and looking at its confidence in contextual representation of objects, determines when to add a new context, or a context layer to form a hierarchy.

A. Related Work

Context Modeling: In AI, McCarthy [4] was known to be the first to define what context is and is not with a modeling perspective. McCarthy’s definitions and formulations were in propositional logic, which was followed by similar attempts using predicate logic or description logics [10], [11]. Such definitions rely on formulating a context in terms of rigid rules and relations between entities, which are difficult to enumerate in practice.

In computer vision and pattern recognition, on the other hand, models integrated context into many problems such as object recognition [12], [13], activity recognition [14] using probabilistic graphical models, such as Markov Random Field, Conditional Random Field, or Bayesian Networks. In these models, contextual information was provided mostly through local interactions between predictions.

In natural language processing, many models (e.g., Hidden Markov Models) have been proposed that incorporated latent variables to model hidden information in the data. These models were followed by newer approaches such as Latent

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Semantic Analysis [15], Latent Dirichlet Allocation [16] that have been widely used for modeling topics (i.e., contexts) of documents, and recently scenes [7].

There are several studies in robotics that integrate context into various robot problems, examples including [17], which used context in grounding natural language to manipulation actions; [18], which used context in determining where to place a new object in the scene; [19], which modeled local interactions between objects (as context) in determining their labels; and, [7], which proposed using context in modulating object detections in a scene and planning. Our model differs from all these studies by being incremental and hierarchical.

**Incremental or Hierarchical Context Modeling:** There are incremental context or topic modeling efforts in text modeling [5], computer vision [20] and in robotics [6], [7]. These methods look at the errors or the entropy (perplexity) of the system to determine when to increment. Moreover, they are not hierarchical. There are also other methods such as Hierarchical Dirichlet Processes [8] or its nested version [9] that assume the availability of all data to estimate the number of topics or assume infinite number of topics, which are both unrealistic for robots continually interacting with the environment and getting into new contexts through their lifetime.

**B. Contributions**

Compared to the existing studies (as briefly reviewed in the previous section), our paper makes the following major contributions:

- An incremental hierarchical (deep) Boltzmann Machine (BM) has been proposed, which, with each arriving new scene, determines to add a new hidden neuron or a hidden layer without making an assumption about the data or the structure.
- We introduce two novel measures to make BM incremental and hierarchical. Our measures mainly capture how strongly a neuron is represented by a hidden neuron in the next layer. This forces (i) a context (hidden neuron) to have at least one object that strongly activates it, and (ii) an object or a hidden layer in the hierarchy to be strongly linked to at least one hidden neuron in the next layer.

We compare our method against Restricted Boltzmann Machines (RBM) [21], incremental RBM [20], incremental LDA [7], Deep Boltzmann Machines (DBM) [22] and show that it performs better in several aspects in scene modeling tasks.

**II. BACKGROUND: GENERAL, DEEP AND RESTRICTED BOLTZMANN MACHINES**

A Boltzmann Machine (BM) [23] is a stochastic network composed of visible nodes \( v = \{v_i\}_{i=1}^V \subset \{0, 1\}^V \) and hidden nodes \( h = \{h_j\}_{j=1}^H \subset \{0, 1\}^H \) — see also Figure 2. Visible nodes and hidden nodes are connected to each other with symmetrical edges with weights \( W = \{w_{ij}\} \) with \( w_{ij} \in \mathbb{R} \). In general BM, there is no restriction on connections, and a node is connected to all other nodes, which, however, makes the learning and the inference problems more challenging and slow. To overcome these limitations, a restricted version of BM (called Restricted Boltzmann Machines [RBM] [21] or Harmonium Networks [24]) has been proposed. Alternatively, as in Deep Boltzmann Machines (DBM) [22], one can form layers of hidden nodes to estimate a more reliable latent model of the data – see Figure 2 for a schematic comparison.

Training an RBM consists of two phases [21]: (i) Positive phase: where data is clamped to the visible units \( v \), hidden units \( h^0 \) are activated, and average joint activations \( \langle v_i h_j \rangle^0 > 0 \) are calculated. (ii) Negative phase: Visible units, call it \( v^1 \), are reconstructed from \( h^0 \), and hidden units, \( h^1 \), are re-estimated from \( v^1 \). From this iteration, average joint activations \( \langle v_i h_j \rangle^1 > 1 \) are re-calculated.

Each weight is then updated by using these joint activations, as follows:

\[
    w_{ij} \leftarrow w_{ij} + \epsilon \times (\langle v_i h_j \rangle^0 - \langle v_i h_j \rangle^1)
\]

**III. OUR MODEL: A DEEP INCREMENTAL BOLTZMANN MACHINE (dIBM)**

In this section, we first describe how we make one layer of incremental RBM (iRBM) and then present deep incremental BM (dIBM).

**A. Incremental Restricted Boltzmann Machines (iRBM)**

Our first contribution is a new way to make RBM incremental. Unlike previous work which uses entropy of the system [6] or the reconstruction error to make an update decision [20], our approach relies on calculating a confidence measure for each visible unit \( v \):

\[
    c_v \leftarrow \max_j w_{vj},
\]

Fig. 2: A schematic comparison of Boltzmann Machines, Restricted Boltzmann Machines and Deep Boltzmann Machines.
which essentially links a visible node’s confidence to how strong it is connected to hidden neurons; if the maximum weight to hidden neurons is low, then the network has not found a suitable strong topic for that visible node yet.

Similarly, we can also define a baseline confidence $c_m^{[h]}$ for the whole model with current hidden neurons $h$, using a softmax function to have a smoother behavior:

$$c_m^{[h]} \leftarrow \frac{1}{Z_0} \exp \left( \min_v c_v \right), \quad (3)$$

with $Z_0$ being the partition function:

$$Z_0 \leftarrow \sum_v \exp(c_v). \quad (4)$$

When the model is fed with new scenes ($v$), over time, the model will slowly fall short in representing $p(v)$ and the model’s current confidence ($c_m^{ curr} \leftarrow 1/Z_0 \exp (\min_v c_v)$) will slightly drift away from its baseline confidence $C_m^{[h]}$. When that happens, a new hidden neuron should be added to increase the model’s capacity. This condition can be formulated as:

$$c_m^{ curr} < t \times c_m^{[h]}, \quad (5)$$

where $t$ is a scaling factor, controlling the system’s patience (empirically set to $\exp(-0.5)$). Note that one can simplify Equation 5 by removing $Z_0$s on both sides.

The new neuron’s weights are initialized as follows:

$$w_{ik} \leftarrow \left( \sum_{j=1}^{[h]-1} w^{ij} \right)^{-1}, \quad (6)$$

which assigns $v_i$’s weight to $h_k$ inversely to the sum of its weights to other hidden neurons; if this sum is large, $v_i$ is strongly represented by these hidden neurons, and its weight $W_{ik}$ to the new hidden neuron should be small. If, on the other hand, the sum is small, $v_i$ is strongly represented by these hidden neurons, and its weight $W_{ik}$ to the new hidden neuron should be big.

The algorithm for incremental RBM is summarized in Alg. 1.

**Algorithm 1: Incremental RBM for a new scene.** Initially, there is only one hidden node, i.e., $|h| = 1$, and $iRBM$ (patience of the model) is set to $\exp(-0.5)$.

**Input:**
- $s$: A new scene (i.e., a $v$ vector, s.t. $v_i = 1$ if $s$ contains object with label $i$)
- $W$, $|v|$, $|h|$: Current model

**Output:** $W$: Updated model

1. Clamp $v$, estimate $h^0$ and calculate $<v_i h_j>^0$ $\triangleright$ Positive phase
2. Reconstruct $v^1$ from $h^0$, estimate re-estimate $h^1$ $\triangleright$ Negative phase
3. Calculate $<v_i h_j>^1$
4. $w_{ij} \leftarrow w_{ij} + \epsilon \times (\langle v_i h_j >^0 - <v_i h_j>^1)$ $\triangleright$ update weights
5. $c_v \leftarrow \max w_{ij}$ $\triangleright$ calculate confidence for visible neurons
6. if $\exp(\min c_v)/Z_0 \times c_m^{[h]}$ then
7. Add a new hidden neuron, let $k$ be its index
8. $w_{ik} \leftarrow \left(\sum_{j=1}^{[h]-1} w^{ij}\right)^{-1}$ $\triangleright$ Initialize new weights
9. $Z_0 \leftarrow \sum_v \exp(c_v)$
10. $c_m^{[h]} \leftarrow \exp(\min c_v)/Z_0$ $\triangleright$ Update baseline confidence for new
11. end $h$

for a hidden layer $f$ when layer $f$ has exactly two hidden neurons:

$$r_f \leftarrow d(h_i, h_j), \quad \text{for } h_i, h_j \in h^f, \quad (7)$$

where $d(h_i, h_j)$ is the distance between $h_i$ and $h_j$ based on their weights:

$$d(h_i, h_j) = \frac{1}{2} \left[ d_{KL}(sm(w^i), sm(w^j)) + d_{KL}(sm(w^j), sm(w^i)) \right], \quad (8)$$

where $w^j = <w_{kj}>$ is the vector of weights connecting $h_j$ to the previous layer’s nodes; and $sm(.)$ is the vector-defined softmax function defined as follows:

$$sm(w)_i = \frac{\exp(w_i)}{\sum_j \exp(w_j)}. \quad (10)$$

After adding more neurons to a hidden layer $f$ (i.e., when $|h^f| > 2$), the layer’s current confidence ($r_f^{ curr} \leftarrow \min_{h_i, h_j \in h^f} d(h_i, h_j)$) drifts away. When that happens, we add a new hidden layer as the next layer of layer $f$. This condition can be defined as follows:

$$r_f^{ curr} < t^{diBM} r_f, \quad (11)$$

where $t^{diBM}$ is a constant controlling the system’s patience to add a new layer with a single neuron. Each neuron in layer $f$ is connected to the single neuron in layer $f + 1$ with random weights.

The algorithm for diBM is summarized in Alg. 2.

**IV. Experiments and Results**

In our experiments, we compare IRBM and diBM against (vanilla) RBM (with the same number of hidden units that was found by iRBM), stacked RBM (with the same number of layers and hidden units as found by diRBM), DBM (with the same number of layers and hidden units as found by diRBM), incremental RBM by Yu et al. [20], and incremental
LDA by Celikkanat et al. [7]. In comparing the methods, we use the same number of epochs for each method.

Note that RBM and DBM are not incremental methods; we test them in batch mode (giving all training data at once) and online (incremental mode where we give scenes on at a time). Moreover, we also test how good our diBM can initialize a vanilla DBM method (shown with DBM ← diBM in the tables) for the tasks used in the paper.

A. Dataset

For training and evaluating the methods, we used the SUN RGB-D scene classification and segmentation dataset [25], which is composed of labeled objects in various scenes. We selected 10,335 scenes by splitting the dataset into two for training (7,000) and testing (3,335).

B. Number of Contexts

We first analyze how many contexts and layers are discovered by the incremental methods and diBM. As shown in Figure 4, where the correct number of contexts (scene categories) is 8. From the figure, we see that iRBM finds the correct number of contexts in Figure 4. Since the figure shows the total number of contexts on all layers, the number of contexts found by diBM, which is 16, is more.

C. Entropy of the Models

We compared the methods based on how the systems’ entropies change over time, where entropy is defined as follows (as in [7]):

$$H = \rho H(o|c) + (1-\rho)H(c|s), \quad (12)$$

where random variables \(o, c\) and \(s\) denote objects, contexts and scenes respectively; \(H(\cdot|\cdot)\) denotes conditional entropy; and \(\rho\) is a constant (selected as 0.5) controlling the importance of the two terms. The first term measures the system’s confidence in observing certain objects given a context, and the second one promotes context confidence given a scene.

Figure 5 displays how the entropies of the incremental models change over time. We see that diBM has discovers a structure with the lowest entropy (we take the mean of its entropy for each layer).

D. Qualitative Inspection of Context Coherence (Hidden Nodes)

To get a feeling of the performance of the methods, we looked at the strongest objects associated with the hidden neurons. For this, we just compared one-layer methods (iRBM, incremental RBM [20], incremental LDA [7] and online vanilla RBM) and hence, not considered DBM, DiBM, stacked RBM or stacked iRBM, since the first layers of these methods (RBM and iRBM) are included in the comparison.

Table I lists the three best (selected by visual inspection) hidden neurons’ strongly connected objects for the different methods. We see that, among the methods, iRBM seems to have found the most relevant objects together in separate contexts. The third hidden neuron of Celikkanat et al. [7] seems to have combined unrelated objects together, and
TABLE I: Most probable 10 objects of best 3 hidden units of a subset of SUN RGBD-Data dataset (8 contexts and 1600 scenes). “d” is indeed a label in the dataset. We do not provide results for DBM, Stacked RBM, Stacked iRBM or diBM since they yield similar results for the first layer, when compared to their single layer counterparts, i.e., RBM and iRBM. (We shortened some words to save space: CM: computer monitor, TPD: Toilet Paper Dispenser, ED: Electrical Device)

| Hidden1    | Hidden2    | Hidden3    |
|------------|------------|------------|
| keyboard   | oven       | sink       |
| mouse      | stove      | toilet     |
| CM         | carpet     | faucet     |
| cord       | countertop | pipe       |
| chair      | toaster    | soap       |
| cpu        | microwave  | tap        |
| monitor    | tilefloor  | cabinets   |
| pillar     | refrigerator| uralin     |
| desktop    | painting   | towel      |
| sink       | painting   | tooth      |
| monitor    | sink       | sink       |
| floor      | floor      | floor      |
| table      | keyboard   | floor      |
| chair      | wall       | wall       |
| wall       | computer   | toilet     |
| desk       | desk       | cabinet    |
| paper      | paper      | counter    |
| door       | door       | door       |
| window     | mouse      | pipe       |
| bookshelf  | bookshelf  | bookshelf  |
| chairs     | window     | microwave  |
| urinal     | keyboard   | floor      |
| toilet     | book       | floor      |
| towel      | monitor    | cup        |
| pipe       | pillow     | minifridge |
| book       | flowers    | lid        |
| sink       | mirror     | refrigeration|
| window     | window     | cabinet    |
| bookshelf  | adapter    | insulatedbag|
| garbage   | wall       | stallsreflection|
| bottles    | floor      | frame      |
| mirror     | counter    | table      |
| sink       | teapot     | chairs     |
| floor      | toaster    | bookcase   |
| window     | coffeemaker| sofa       |
| plumbing   | wall       | ED         |
| mop        | carrier    | triangle   |
| towel      | stove      | classplate |
| wall       | light      | dress      |
| counter    | d|        | glass      |
| toilet     | cupboard   |             |

incremental RBM [20] and online vanilla RBM yielded worst results.

E. Partially Damaged Scene Reconstruction

To test how good the models have learned the data distribution, we generated partially-corrupted \( \mathbf{v} \) from \( \mathbf{v} \in \mathbf{V} \), and we compared methods’ reconstruction \( \mathbf{v}' \) of the visible vector. For corrupting the visible nodes, we selected \( \alpha \) dimensions in \( \mathbf{v} \) arbitrarily and flipped those dimensions with probability 0.5.

For evaluating the methods, we devised the following measures:

\[
\text{CD} = 1 - \frac{\sum_{\mathbf{v} \in \mathbf{V}} \sum_{i} a(v_i - v'_i)}{|\mathbf{V}| \times |\mathbf{V}|},
\]

(13)

\[
\text{CDa} = 1 - \frac{\sum_{\mathbf{v} \in \mathbf{V}} \sum_{i} a(v_i - v'_i)}{|\mathbf{V}|},
\]

(14)

where \( \text{CD} \) and \( \text{CDa} \) respectively are acronyms for Corrupted Dimensions and Corrupted Data; and, \( a(\cdot) \) is the absolute value function. Note that \( \text{CDa} \) and \( \text{CD} \) can take negative values if a method destroys more than it successfully reconstructs.

We noticed that, while trying to recover the corrupted bits, some methods destroyed the uncorrupted parts as well. To be able to measure this, we devised alternative versions:

\[
\text{CDb} = 1 - \frac{\sum_{\mathbf{v} \in \mathbf{V}} \sum_{i} a(u_i - u'_i)}{|\mathbf{V}| \times |\mathbf{V}|},
\]

(15)

\[
\text{CDa} = 1 - \frac{\sum_{\mathbf{v} \in \mathbf{V}} \sum_{i} a(v_i - v'_i)}{|\mathbf{V}|},
\]

(16)

where \( \mathbf{u} \) is the corrupted part of \( \mathbf{v} \).

Table II lists the accuracies for the different methods. We see that, among the batch methods (that use all data at once), stacked RBM performs best, in fact better surprisingly better than DBM or DBM initialized with diBM weights. This suggests that stacked RBM can converge faster than these methods.

When we look at the performances of the incremental methods, we see that diBM yields the best results, not
only better than its incremental competitors but also the batch methods. Comparing iRBM with RBM (both batch or incremental), we see significant difference in terms of performance.

Comparing iRBM with RBM, stacked iRBM with stacked RBM, and diBM with DBM from Table II, main conclusion is that our methods converge (incrementally) to a model that is assumed to have a given structure. This suggests that, with methods like ours, we can build (evolve) models through time that perform as good as (and in fact, better than) their rigid counterparts. This alleviates the problem of model (structure) selection before or while training models.

See Figure 6 for an example corrupted and reconstructed scene.

V. CONCLUSION

We have proposed two new methods in the paper: (i) one method to incrementally construct a layer of RBM by pushing hidden neurons to favor a subset of the objects, and vice versa, and (ii) another method to incrementally add hidden layers with each arriving scene to construct a deep incremental BM. Compared to baseline methods and other methods in the literature, we showed in the SUN RGB-D Dataset that our methods construct better models in learning a distribution of the data, as shown by the correctly found number of contexts, the low entropy, the reconstruction of the corrupted data and visual inspection of what the hidden neurons represent.

ACKNOWLEDGMENT

This work was supported by the Scientific and Technological Research Council of Turkey (TÜBİTAK) through project called “Context in Robots” (project no 215E133).

REFERENCES

[1] H. Celikkanat, G. Orhan, N. Pugeault, F. Guerin, E. Sahin, and S. Kalkan, “Learning and using context on a humanoid robot using latent dirichlet allocation,” in *IEEE ICDL-EpiRob*, 2014.

[2] W. Yeh and L. W. Barsalou, “The situated nature of concepts,” *The American journal of psychology*, pp. 349–384, 2006.

[3] L. W. Barsalou, “Simulation, situated conceptualization, and prediction,” *Philosophical Transactions of the Royal Society B: Biological Sciences*, vol. 364, no. 1521, pp. 1281–1289, 2009.

[4] J. McCarthy, “Notes on formalizing context,” *International Joint Conference on Artificial Intelligence*, pp. 555–560, 1993.

[5] K. Canini, L. Shi, and T. Griffiths, “Online inference of topics with latent dirichlet allocation,” in *Artificial Intelligence and Statistics*, 2009, pp. 65–72.

[6] M. G. Ortiz and J.-C. Baillie, “Incremental training of restricted boltzmann machines using information driven saccades,” in *IEEE ICDL-EpiRob*, 2014.

[7] H. Celikkanat, G. Orhan, N. Pugeault, F. Guerin, E. Şahin, and S. Kalkan, “Learning context on a humanoid robot using incremental latent dirichlet allocation,” *IEEE Transactions on Cognitive and Developmental Systems*, vol. 8, no. 1, pp. 42–59, 2016.

[8] Y. W. Teh, M. I. Jordan, M. J. Beal, and D. M. Blei, “Hierarchical dirichlet processes,” *Journal of the American Statistical Association*, vol. 101, no. 476, pp. 1566–1581, 2006.

[9] J. Paisley, C. Wang, D. M. Blei, and M. I. Jordan, “Nested hierarchical dirichlet processes,” *IEEE PAMI*, vol. 37, no. 2, pp. 256–270, 2015.

[10] S. BuvaE and I. A. Mason, “Propositional logic of context,” in *Proceedings of the eleventh national conference on artificial intelligence*, sn, 1993.

[11] S. Klarman and V. Gutiérrez-Basulto, “Description logics of context,” *Journal of Logic and Computation*, p. ext011, 2013.