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# TESTING SIMPLE NEURON MODELS WITH DENDRITES FOR SPARSE BINARY IMAGE REPRESENTATION

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# ТЕСТУВАННЯ ПРОСТИХ МОДЕЛЕЙ НЕЙРОНА З ДЕНДРИТАМИ ДЛЯ РОЗРІДЖЕНОГО БІНАРНОГО ПРЕДСТАВЛЕННЯ ЗОБРАЖЕННЯ

This paper deals with the problem of information representation into a form that allows to make associations, measure similarity and integrate new information with respect to previously stored. Several simple models for encoding information into sparse distributed representation are explored. These models based on the idea that information about stimuli is stored in the population, not an individual neuron, thus each neuron learns many partial features. Results show formation of a sparse representation of image data with high overlap for similar images. Each cell develops multiple receptive fields that together create a population receptive field. It was possible due to incorporation of dendritic tree into standard neuron model. Also, models were tested on a classification of handwritten digits from MNIST dataset. Results from unsupervised representation show poor accuracy compared to the state-of-the-art supervised methods, however, due to the presence of interesting properties further development of an idea should be continued.

**Keywords:** dendritic computation, sparse representation, sparse coding, unsupervised learning.

Стаття розглядає проблему представлення інформації у формі, яка дозволяє створювати асоціації, вимірювати схожість та інтегрувати нову інформацію відносно раніше збереженої. Досліджуються декілька простих моделей для кодування інформації у розріджено розподіленому представленні. Моделі ґрунтуються на ідеї, що інформація про стимули зберігається в популяції, а не в окремому нейроні, тому кожен нейрон навчається на багато часткових ознак. Результати показують формування розрідженого представлення зображення з високим перекриттям для подібних зображень. Кожна клітина формує кілька рецептивних полів, які разом утворюють популяційне рецептивне поле. Це стало можливим завдяки включенню дендритного дерева в стандартну модель нейрона. Також моделі були перевірені на здатність до класифікації рукописних цифр з набору даних MNIST. Результати для навчання без учителя мають погану точність у порівнянні з сучасними методами для навчанням з учителем, однак завдяки наявності цікавих властивостей подальший розвиток ідеї має бути продовжений.

**Ключові слова**: дендритні обчислення, розріджене представлення, розріджене кодування, навчання без учителя.

## Introduction

One of the main problem facing before an intelligent machines creation is finding of a correct substrate of memory [1]. The question how to encode information and in which form it should be stored for efficient further processing remains unanswered. A good candidate for such substrate is hyperdimensional binary vectors [2], [3]. Vectors with dimensions at the order of 1000 provide a good framework of how to associate, compare and bind information of different objects. However, an open issue remains how to form such binary vectors from real-world raw data, such as intensities of pixels, words, and sounds [4].

The standard way to encode something is to create a dictionary, correspondence between feature and its binary code, like latter "A" encoded with 1000001 according to

 

ASCII. This strategy shaped our modern computer science and even was applied to computer vision problems when a set of features, like the shape of an eye, were handcrafted and represented with appropriate binary code. However, biological organisms do not have specified dictionary, they create an internal representation of an environment by themselves through self-organizing neural networks. If we want to create systems with artificial intelligence, we should abandon specified dictionaries by humans and provide an ability to self-generate code of the world.

Recently, it became possible to learn features from raw sensory data by using artificial neural networks through supervised learning. Deep convolutional networks use small kernels for the lower layers that through backpropagation become feature detectors [5]. However, these systems as well require humans to specify dataset and correct labels in contrast to biological neural networks that use a mixture of an unsupervised and reinforced learning.

Another prominent result came from the field of sparse coding. It was shown that under a constraint to reliably reconstruct an input image with using a small part of a dictionary system forms features that resemble receptive fields of simple cells in a visual cortex [6]. Later, more works appeared that provided framework to form biological plausible features and adopting a strategy of sparse coding [7]–[9]. There are two main problems with this approach. The first is that it requires solving the optimization problem in order to generate features in contrast to biological organisms that uses self-organization. This leads to complications in implementing online learning algorithms for practical application in robotics, though recently there was a progress in this direction [10]. The second is that input is reconstructed using real-valued coefficients, thus it restricts to use framework for hyperdimensional vectors [3].

The closest models to form desired representation were developed by Foldiak [11] and Numenta team[12]. They achieved forming a sparse binary representation of an input with feature learning and homeostatic principles. Nevertheless, in these models cells learn to represent a limited set of features, thus it limits representation capacity of the network.

The goal of this work is to test simple models that form a sparse representation of image data based on a dendritic neuron model. These models enable to encode multiple features by a single neuron that increases a capacity of the network and an information is spread across a population of neurons. Also, I provide biological background behind an idea to include dendrites. Models were developed in order to satisfy requirements to work online, thus excluding solving an optimization problem and to provide a large capacity through spread features across a population.

The results show the reconstruction of an image into a sparse distributed representation with high overlap for similar images. Each cell forms multiple receptive fields and together with other cells form population receptive field. However, unsupervised models show poor classification accuracy (0.7) compared to supervised state-of-the-art methods (0.99). This could be due to bad feature extraction; thus it works similarly to comparison to mean image. Despite, that presented results are worse than existing, proposed ideas are not fully investigated and further research to be conducted.

The following paper structured as follows. Next, I provide motivation of the work and its place in a global context. In the “Methods” section, I describe computational models that were used. In “Biological background”, I provide computational properties of the dendritic tree, stressing that standard model of an artificial neuron should be extended.

 

In "Result" section, I provide figures of pattern representation, patterns overlap and results of classification accuracy for MNIST dataset for different models. In the end, I discuss possible reasons for a poor accuracy and future directions of a research.

**Motivation**

The first and important step that biological organisms do is making a representation of raw sensory data from an environment into the form of sparse distributed representation. Recreating this in algorithms will allow to apply efficient association learning and to use properties of high-dimensional binary vectors. In this form, it will be convenient to check information similarity simply by computing hamming distance or, in other words, patterns overlap. As well it will be possible to make sequential memory and to experiment with an action-perception loop. It will be feasible to use reinforcement learning to select right action through sculpturing patterns of activation and efficiently predict an outcome of a planned action. In order to use all of these in real time robotics, it is necessary to develop an algorithm for sparse coding that works online and that are adaptable to a new incoming stream of data.

**Methods**

Handwritten digits from MNIST database were used as an input with applying thresholding and binarizing. As a result, were obtained binary vector $x$ of size 28*28=784.

Representation layer $y$ was initialized with size nxn and random binary weights to input layer. Two connection schemes were used, one with random connection all-to-all with certain percentage $q$ of connected weights ($w_i = 1$), another, with local connections topographically projected from input to representation layer (Fig.1). Activation is calculated according to:

$$y_i = \sum_j w_{ij} x_j + A \sum_k g\Big(\sum_j c^i_{kj} x_j\Big) \qquad 1. \qquad (1)$$

Where $g(z) = \{1,\ if\ z > \theta, and\ 0, otherwise\}$, $\theta$ is a threshold for activation from clustered synapses, A - constant for regulation of an influence of dendrites, and $c^i_{kj}$ stores synapses in clusters. After $y$ is computed was performed k-WTA operation, when k highest values of $y$ were set to one and other to zero. Typically value of k was set small $k = 0.1\|y\|$ compare to size of $y$ in order to achieve sparse representation. Result was a sparse binary vector $y$.

Learning procedure realizes through learning clusters. Pseudocode is presented below.

```
for x in images
        for i in y_size
            for j in x_size
            # retrieval of activation
              y_i = W_ij*x_j
              for k in y_clusters
                  y_i = y_i + g(sum_j(c_ijk*x_j))
         y = k_WTA(y)
         # learning clusters
         for i in nonzero(y)
            k = number_of_stored_clusters + 1
            cluster = select random S indices of active x_j
            c_ijk = 1 where j in cluster
         return y
```

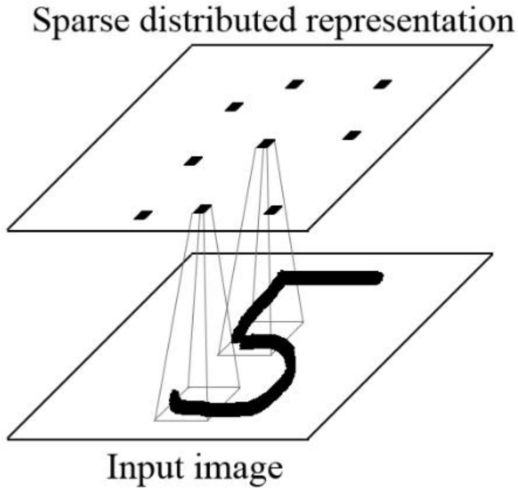


Fig.1. Schematic image of connections

After obtaining a representation for every image it is possible to count pattern overlap between for different representations. Pattern overlap for two binary vectors we define as Hamming distance.

To calculate accuracy every representation of test image was compared to mean pattern for all training images from the same class. The highest overlap of patterns determines to what class belongs representation for the test image.

**Biological Background**

The main idea of this paper is to include dendritic computation into neuron model and to try to receive a sparse representation of raw sensory input based on this model. First artificial neural networks were inspired by knowledge from biology and were based on information available 70 years ago. Now we know much more about real neuron functioning and today we acknowledge the importance of dendritic tree. Synapse from thousands of neurons terminated on a vast dendritic tree of a single neuron and it is very important to which part of dendrite each synapse is connected and what are neighboring synapses. Presence of dendrites makes possible to integrate input not just linearly, as it was previously assumed, but supra- and sub-linearly (Fig.2B) [13]–[15]. Thus, a small amount of active neighboring synapses could elicit dendritic spike and depolarize the cell much larger than if these synapses were distributed on different branches of dendrites (Fig.2A) [16], [17]. Such close synapses form clusters and the possible computational role for this is to track coincidence of an activation of particular neurons [18]. Every neuron has a lot of such clusters thus neuron works as a multiple feature detector. This is in good correspondence with population coding, where information encoded not in individual neurons but shared across the population. Every neuron can take part in different populations thus it needs to learn connections to many populations and clustered synapses on dendrites makes it possible. This differs from classical Hebbian learning where connection increases or decreases between two neurons and tracks pair-wise correlation. In this approach, neuron learns higher-order correlations and connections occur not between individual neurons, but between populations.

 

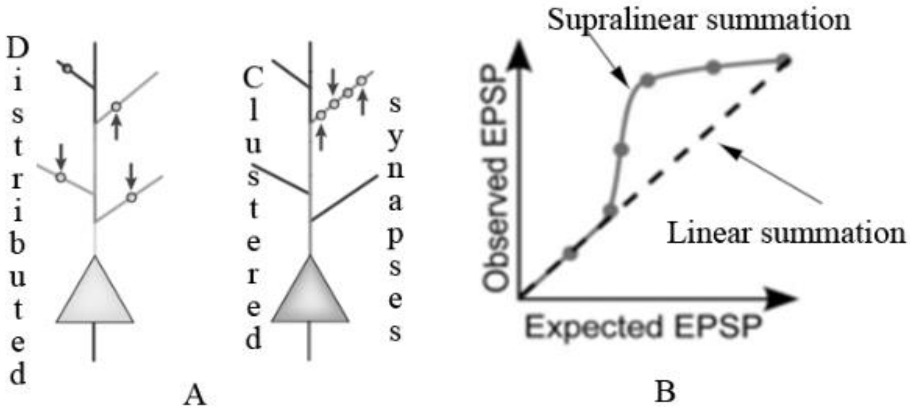


Fig. 2. **A)** The depiction of distributed synapses on the left and clustered on the right side. Modified from [19] **B)** Difference between linear and supralinear summation.

In this paper, I try to simulate this ability of a neuron to learn higher-order correlations and to be sensitive to multiple features. It was shown that such ability increases the capacity of association memory (results in publishing), but here I check if it helps with the sparse representation of a sensory data.

**Results**

Proposed methods are capable to generate sparse binary vectors from image due to applying k-WTA. In order to see if similar patterns generate similar code pattern overlap was computed. On Fig.3A presented results for pattern overlap for four different digits, the darker the higher overlap. The figure shows that digits from same class have higher overlap, however, this distinction is not totally clear. There are instances that have high overlap from different classes. This interclass high overlap was the main reason for bad classification accuracy, that will be described later.

Next, the idea of information spread across population was tested. On Fig.4A presented collection of receptive fields of encoding cells and on the right overall receptive field of a population. On Fig.3B presented more images of population receptive fields, which was computed as the linear sum of receptive fields of individual neurons.

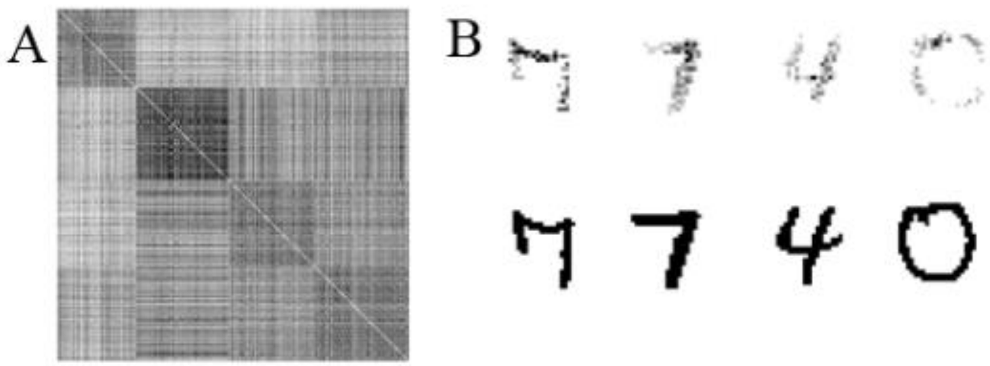


Fig. 3. **A)** Overlap of patterns from different images. Black shows high overlap. Visible black squares represent overlap for patterns from similar images from one class. **B)** Lower: binary images from handwritten digits. Upper: receptive field of an entire population

The main deviation of proposed models from the standard is that each neuron has multiple receptive fields computed by dendrites. On Fig.4B presented such collection of receptive fields of single cell and on the right combined total receptive field. Importantly, that these receptive fields determine activation not through linear summation, but as a threshold $\theta$ for coincident detection. This result is very similar to coarse coding [20], [21], where cells have very wide or coarse receptive field but on the level of population it is possible to decode precise stimulus.

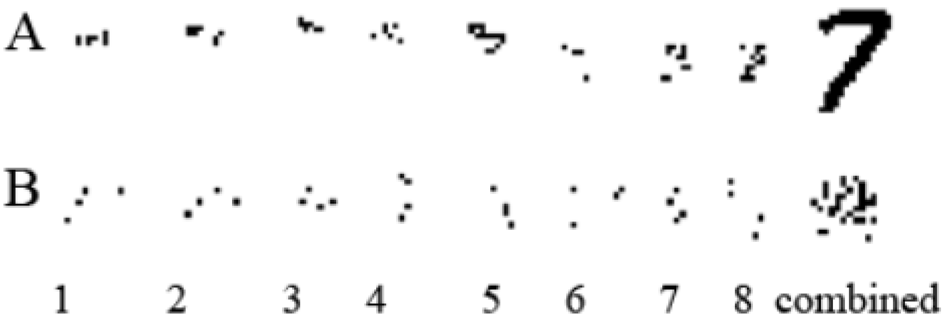


Fig. 4. **A)** Image and receptive fields of individual cells that encode digit. Receptive field took from activated clusters. **B)** The receptive field of individual clusters for one cell and combined receptive field. It looks like coarse coding.

Also, there were performed tests for classification accuracy. For all images from the same class was computed average representation vector. It was done for every class and as result 10 mean representation vectors were obtained. Then, representation for every image from test set was compared to each mean representation by calculating overlap. The highest overlap determined the recognized class. To test accuracy were used a different configuration of a model: with random connections, with localized connections, with clusters of activation that produce multiple receptive field and model without clusters, merely linear activation, and k-WTA. All four showed similar results with accuracy near 0.7. The same accuracy could be obtained just by comparing the image to mean images without any representation into a binary vector. This tells that features extracted for binary representation is not properly learned and representation works just like image transformed into a different form.

**Conclusions**

This paper deals with the problem of information representation into sparse distributed representation in order to use hyper dimensional computing framework. Existing solutions do not fully satisfy all requirements, they lack online learning, or use real values, or they have low capacity. The proposed idea is to use the extended model of a neuron that includes dendritic computation to achieve sparse data representation. It is assumed that the goal of dendrites is to track coincidence in incoming stimuli, not merely linear summation. This allows to be responsive to many features that is crucial for having a large capacity of the network.

Proposed models form sparse representation with high overlap for similar images. Also, cells were able to form many partial receptive fields using dendrites. Information about the image was spread across the population that forms combined receptive field. Furthermore, each cell forms many receptive fields that together form much wider field. This relates to an idea of coarse coding presented 30 years ago [21] but was not elaborated further.

 

Achieved result for classification accuracy with unsupervised representation is near 0.7. This is significantly worse than state-of-the-art learning algorithms with accuracy more than 0.99. Even simple KNN algorithm gives more than 95% of correct predictions. However, presented idea shows interesting properties like population receptive field, coarse coding, multiple receptive fields for a neuron and worth to be developed further. The reason why accuracy is low could be an absence of inhibition, thus receptive fields are all positive that leads to false activation. Also, it is possible that to receive higher accuracy it is not sufficient to compare representation from the first layer, maybe hierarchical architecture will form more stable representation for similar inputs.

Overall, it forms desired properties: neuron works as multiple pattern detector, information about an input is encoded into the whole population and it creates sparse code. However, there is a high overlap between patterns from different classes that limits classification accuracy and suggests bad feature extraction. More research is needed in this direction.

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## РЕЗЮМЕ

**В.М. Осауленко**

**Тестування простих моделей нейрона з дендритами для розрідженого бінарного представлення зображення**

В даній роботі розглядаються моделі нейрона з урахуванням дендритного дерева. Це мотивовано нещодавніми дослідженнями роботи біологічного нейрона та обчислювальних властивостей дендритного дерева, де показано, що нейрон в цілому має значно більшу обчислювальну здатність ніж вважалося раніше. В комбінації з ідеєю розрідженого кодування показано можливість нейрона формувати багато рецептивних полів на основі зображень рукописних цифр. Кожне рецептивне поле записується на окремому дендритному сегменті і зберігає часткові риси вхідних даних. Хоча й об'єднане рецептивне поле одного нейрона не має селективності, але вона виникає на рівні популяції, що добре узгоджується з ідеєю грубого кодування. Таким чином зображення були закодовані у розріджене представлення нейронної мережі, де кожен нейрон навчений на широкий спектр стимулів. Також було випробувано ефективність кодування в задачі класифікації рукописних цифр. Досягнута точність менша ніж у інших методів на основі навчання з учителем, що свідчить про необхідність або збільшення розміру рецептивного поля нейрона з додавання пригнічуючих нейронів, або додавання нових шарів нейронів. Розріджене кодування з урахуванням дендритів має більш біологічну реалістичність та обчислювальну перевагу, так як дає змогу зменшити кількість нейронів. Зменшення кількості біологічних нейронів в мозку людини виникає в наслідок оптимізації ресурсів, та зменшення нейронів в моделі має перевагу у оптимізації ресурсів у випадку імплементації алгоритму в електронних приладах.

*Надійшла до редакції 30.10.2017*

 