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## Hybrid learning net: a novel architecture for fast learning

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### Abstract

Currently, neural networks have succeeded in object recognition tasks based on images, natural language translation, and voice recognition, to name a few. However, neural nets are customly built for different applications and vary a lot in architectures and model hyperparameters like learning rate and parameter initialization, what's worse, these hyperparameter settings generally play a big role in performances of training and testing, and the best settings for specific applications are so far only available by manually repeatedly trying different configurations which is really huge work. We, thereby, present a novel neural network architecture, called Hybrid Learning Net(HLN), with Self Organizing Maps(SOMs) embedded in each layer to learn from samples in **both** unsupervised and supervised way, targeting to achieve a much **faster** net learning for general applications with **good** robustness to a few key hyperparameters such as the parameter initialization and the net strcuture variation. We've also experimented our architecture over the MNIST dataset, it has proved the impressive improvement on both training and testing phases of general applications, say compared to the traditional architecture, our method speed up the training process by up to **40** times, which only take **1** epoch to get an testing accuracy of over **87.5%**, and takes no more than **3** epoches to reach a profound accuracy of over **91.3%**. In addition, on big scale of input dimension and/or with deeper architecture, where the traditional architecture fails to learn at all, our method still have a fast learning, and can retrieve the same testing accuracy on MNIST. Moreover, we have discovered some interesting facts about neural network trainings, such as neuron activation sparsity is strongly correlated to the training loss within certain cases which may shed a little light on how such architecture really works.

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**Keywords:** hybrid learning; neural network; general application; sparsity; SOM; MNIST; fast learning

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### 1. Introduction

Since the first mathematical model of artificial neural network was proposed in 1943[1], the neural network has been designed into many architectures, such as Convolutional Neural Networks(CNNs) for image recognition [2], Recurrent Convolutional Neural Networks(R-CNNs) for object detection in videos[3], and Long Short Term Memorys(LSTMs) for speech recognition [4] and many, many more to make it a list. These specially designed neural network models are trained by lots of efficient methods with tons of carefully chosen little skills which we may call tricks. Such neural network architectures suit well for their specific applications but may have plain or worse performances on others, and their best performances rely heavily on hyperparameter configuration in

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general. Thus, it is an in-demand job to propose a relatively universal architecture that enables equal or similar performances among varied applications.

We notice that, although there're plenty of choices to train a neural network, literally all these methods can be reduced into 3 categories, supervised learning [5], unsupervised learning [6], and the semi-supervised [7]. In supervised learning, one can only train a model from labeled samples, however in real applications, labeling a large dataset is a tough and costly task, the unlabeled ones are therefore the primary data available. To make use of the majority unlabeled data, a few unsupervised training algorithms arose. These unsupervised learning methods, denoted as pretraining, attempt to produce an optimized parameter initialization [8]. Thus such unsupervised techniques can only be applied before the supervised training phase, once the supervised begins, the unsupervised learning will become unavailable for the model. While the semi-supervised learning allows the model to learn from both labeled and unlabeled samples at the same time, however they use a regularizer to embed the semi-supervised learner to original optimizing object, and generally a balance constraint is required to avoid the trivial solution [9]. Such an enhanced learner brings more hyperparameters (say the balance constraint), making it even more difficult to search for best settings for current architectures. Additionally, this integration way makes it impossible to separate the two learners as the semi-supervised regularizer is built on the supervised learner, and therefore requires an early supervised training alone with profound labeled data before the semi-supervised regularizer can be applied. Thus we introduce a new architecture that learn in both supervised and unsupervised ways at the same time, and requires no extra techniques on training. Our architecture, Hybrid Learning Nets (HLNs), made of stacked layers, with each hidden layer embedded with a Self Organizing Map (SOM), training in the simplest way of backprop, demonstrate much faster learning capability and remain robust to parameter initialization and network configuration such as the net depth of layer.

The main contributions of our work are:

- We propose HLN, a SOM-embedded architecture to learn both unlabeled and labeled data at the same time.
- Our architecture HLN overcomes the problem brought by traditional semi-supervised learning methods that the semi-supervised learning requires an early standalone training for the supervised learner which contradicts with the key condition: no enough labeled data is provided.
- The HLN uses a SOM embedding coupling the first hidden layer near to the input layer, to learn a cluster mapping function from the cheap and massive unlabeled data, and this process can occur at any time, no matter the supervised learning begins or not, they're completely separated. For deeper hidden layers, each of them also has a SOM-embedding coupled, but can only learn from labeled data.
- The experimental result shows HLNs speed up the whole training a lot.
- Our architecture demonstrates a good robustness to some hyperparameters which may slightly relax the work of manually searching for best settings of hyperparameters by repeatedly trying different configurations and run the whole training and testing over and over again.

HLN is implemented in Python and all our code and results of experiments in detail are available at <https://github.com/hiroki-kyoto/hybrid-learning-net>

The rest of the article is as follows. In section 2 we describe existing semi-supervised algorithms for neural network models, recall the SOM and explore a different training method for SOM when applied in the neural network embedding. In section 3, we introduce our novel architecture HLN, show how to embed SOMs into deep architectures of neural net. In section 4 we explain the exact training theory for HLNs. Section 5 gives experimental comparisons between nets with HLN architecture and without, and the last section concludes.

## 2. Related work

### 2.1. Semi-supervised learning for neural network

A key assumption in semi-supervised algorithms developed so far, is the structure assumption: two samples with similar distribution on the same mapping structure tend to have high probability of belonging to the same class. Based on this assumption, one can use large unlabeled data to uncover such structures. There're already a few algorithms dedicated to do this, such as cluster kernels [10], Low Density Separation (LDS) [11], label propagation [12], to name a few. In such algorithms, designing a regularizer to enable the model to learn the

representation or structure of raw data, in order to improve the supervised learning performance, becomes the key point.

To get a clear idea of how such semi-supervised learning algorithms work, we will give a brief recall to some. Let's firstly focus on the general algorithm description of semi-supervised learning. Given a set of unlabeled samples,  $\mathbf{X} = \{x_1, \dots, x_N\} (x \in \mathbb{R}^d)$ , and the similarity labels between any  $x_i$  and  $x_j$ ,  $\mathbf{W} = \{W_{ij} | i, j = 1, \dots, N\}$ , we're to find the best embedding function,  $f(x)$ , for each sample  $x_i$ , to minimize:

$$\sum_{i=1}^N \sum_{j=1}^N L(f(x_i), f(x_j), W_{ij}) \quad (1)$$

to explain it,

- $L(\cdot)$  is the loss function of 3 variables:  $\langle f(x_i), f(x_j), W_{ij} \rangle$ , such as

$$L(f(x_i), f(x_j), W_{ij}) = \max(0, \|f(x_i) - f(x_j)\| - W_{ij})$$

- $f(x) \in \mathbb{R}^n$  is the embedding function, it tries to produce a vector from  $x_i$ , similar to that of  $x_j$  with  $W_{ij} = 0$ , and dissimilar with  $W_{ij} = 1$ .
- $W_{ij} \in \mathbb{R}$  is the similarity label of the sample pair  $\langle x_i, x_j \rangle$  from  $\mathbf{X}$ .

## 2.2. Tables

All tables should be numbered with Arabic numerals. Headings should be placed above tables, left justified. Leave one line space between the heading and the table. Only horizontal lines should be used within a table, to distinguish the column headings from the body of the table, and immediately above and below the table. Tables must be embedded into the text and not supplied separately. Below is an example which authors may find useful.

Table 1. An example of a table.

An example of a column heading	Column A (t)	Column B (T)
And an entry	1	2
And another entry	3	4
And another entry	5	6

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References should be added at the end of the paper, and its corresponding citation will be added in the order of their appearance in the text. Authors should ensure that every reference in the text appears in the list of references and vice versa. Indicate references by [1], [2-3] in the text. The actual authors can be referred to, but the reference citation(s) must always be given. Some examples of how your references should be listed are given at the end of this template in the 'References' section, which will allow you to assemble your reference list according to the correct format and font size.

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Section headings should be left justified, with the first letter capitalized and numbered consecutively, starting with the Introduction. Sub-section headings should be in capital and lower-case italic letters, numbered 1.1, 1.2, etc, and left justified, with second and subsequent lines indented. You may need to insert a page break to keep a heading with its text.

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Avoid hyphenation at the end of a line. Symbols denoting vectors and matrices should be indicated in bold type. Scalar variable names should normally be expressed using italics. Weights and measures should be expressed in SI units. Please title your files in this order conferenceacronym\_authorslastname.pdf

### 3. SOMs-embedding for deep architecture

A recall to SOMs.

How we construct deep architecture with SOMs-embeddings.

### 4. Empirical Study

To test our architecture performance on small data, we use a synthetic dataset containing 3.5% noisy samples. A sampling from this dataset get the

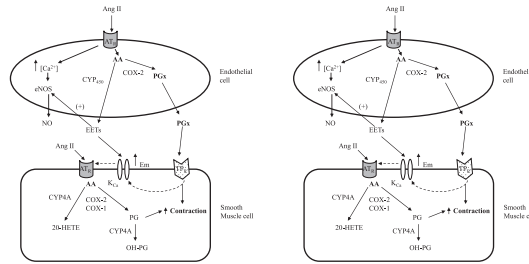


Fig. 1. (a) first picture; (b) second picture.

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Equations and formulae should be typed and numbered consecutively with Arabic numerals in parentheses on the right hand side of the page (if referred to explicitly in the text),

$$X_r = \frac{\dot{Q}_{rad}''}{(\dot{Q}_{rad}'' + \dot{Q}_{conv}'')} \quad (2)$$

$$\rho = \frac{\vec{E}}{J_c(T = \text{const.}) \cdot \left( P \cdot \left( \frac{\vec{E}}{E_c} \right)^m + (1 - P) \right)}$$

They should also be separated from the surrounding text by one space.

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The citation must be used in following style: [13], [14], [15], [16] and [17].

## Acknowledgements

These and the Reference headings are in bold but have no numbers. Text below continues as normal.

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## Appendix A. An example appendix

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### *Appendix A.1. Example of a sub-heading within an appendix*

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