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Multilayered neural network with structural lateral inhibition for incremental learning and conceptualization

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ABSTRACT

Distributed connectionist networks have difficulty learning incrementally because the representations in the network overlap. Therefore, it is necessary to reduce the overlaps of representations for incremental learning. At the same time, the representational overlaps give these networks the ability to generalize. In this study, we use a modified multilayered neural network to numerically examine the trade-off between incremental learning and generalization abilities, and then we propose a novel network model with structural lateral inhibitions to reconcile the two abilities. We also analyze the behavior of the proposed model using Formal Concept Analysis, which reveals that the network implements "conceptualization": differentiation and meditation between intensional and extensional representations. This study suggests a new paradigm for the traditional question, whether representations in the brain are distributed or not.

1. Introduction

Distributed vs. grandmother cell representation is a traditional but still significant problem because it directly affects the two abilities of generalization and incremental learning. For this problem, we provide a new alternative aspect *conceptualization*: differentiation and mediation between extensional and intensional representations, and demonstrate this idea by implementing and evaluating structural lateral inhibition in a neural network.

It is well-known that incremental learning is difficult for distributed connectionist networks (French, 1999). Here, incremental learning is a task to sequentially learn a data set after learning another data set. In terms of brain plasticity, it is important for such a learning task to be possible. Connectionist networks, such as a multilayered neural network, employ distributed representations, that is, the networks retain memories of what has been learned by using the entire network. Therefore, existing memories are overwritten with new memories. This phenomenon is referred to as catastrophic interference or catastrophic forgetting. It is a radical manifestation of the so-called *stability-plasticity* problem (Carpenter and Grssberg, 1988; Grossberg, 2013).

There are some attempts to modify neural networks to learn incrementally (Williamson, 1996; Mandziuk and Shastri, 1999; Yamaguchi et al., 1999; Fu et al., 2001; Fukushima, 2004; Ozawa et al., 2005; Norman et al., 2005). The architecture in those attempts can be divided roughly into two groups. In one type of architecture, the training data are classified before inputting the data to the network, and the new data is learned by using a different part of the network from the part that retains the existing memories. In the other type of architecture, some or all of training data that had been given are stored, and the new data is learned with the stored data. However, both architectures need a mechanism different from the network, and the network mechanism and its physiological validity are unknown.

In their research on networks that perform incremental learning themselves, Ohta and Gunji (2006) have proposed a network model with lateral inhibitions or presynaptic inhibitions. In this model, representational overlap is reduced by using Winner-Take-All method, destruction of existing memories is prevented by learning based only on negative reinforcement (Chialvo and Bak, 1999; Bak and Chialvo, 2001), and differential sensitivity is enhanced by weight conservation and pre-synaptic inhibitions. As a result, this model succeeds in incremental learning of sequence patterns. As for a realistic neuron model for incremental learning, Ohta et al. (2011, 2012) have proposed an incremental learning model that is based on the Izhikevich model with the spike timing dependent plasticity (Izhikevich, 2006) and parameters of the striatal medium spiny neuron (Humphries et al., 2009). In this model, they numerically examine the effect of lateral inhibitions dependent on pre-synaptic $GABA_B$-R for incremental learning tasks. Uragami et al. (2010) have also proposed an incremental learning model, which is based on the maximum operation in dendrites of neurons. In this model, the

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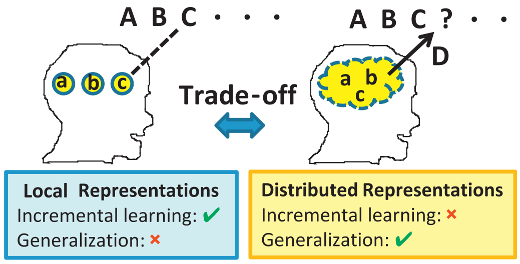

Fig. 1. Are representations in the brain distributed or not? There is a trade-off between incremental learning and generalization abilities.

dendritic computation enhances the differential sensitivity of input patterns. In addition to this, it is an advantage for reducing the representational overlaps, since the number of dendrites is large, as compared to neurons.

In the above models, reducing the representational overlap enables the network to carry out incremental learning. On the other hand, the representational overlap brings generalization ability to the network (Rumelhart et al., 1986). Here, generalization is estimating unknown data form given data. It is important that distributed connectionist networks have generalization ability. However, reducing the representational overlap is accompanied by a decrease in the ability to generalize. In other words, there is a trade-off between the ability to learn incrementally and the ability to generalize (see Fig. 1). Thus, developing network architecture for reconciling incremental learning and generalization is a significant challenge. We propose that the process reconciling incremental learning and generalization is conceptualization – the generation of concepts in the mediation between intent and extent (Ganter and Wille, 1996; Gunji et al., 2001).

The extent is the set of elements included in the concept. The intent is the concept-specifying attribute. Usually the extent and intent are consistent. An example of concept is *even number*. The extent is $\{2, 4, 6 \ldots\}$ and the intent is $\{x| \ x = 2n\}$, and these are consistent. In learning, training data given individually can be interpreted as the extent, while the function that generalizes the data can be interpreted as intent. Memories of previously given data are not overwritten as long as the network locally retains the memories as the extent. On the other hand, a network can generalize precisely when memory is retained as intent by using the whole network. In incremental learning, these are not consistent. Therefore, it is necessary to mediate between learning intent and learning extent.

In the next section, we propose two types of lateral inhibitions: global lateral inhibition (GLI) and structural lateral inhibition (SLI), and implement each in a modified multi-layer neural network. Our proposed models are incremental learning models based only on lateral inhibitions; the models are very simple and, as an essential concept, have physiological significance. GLI network has a parameter which determines the degree of representational overlap. SLI network assumes the mediation between two neuron groups. In Section 3, we numerically examine the learning performance of the proposed network models. The GLI network shows the relationship between the range of inhibitions and the incremental learning and generalization abilities. The SLI network reveals a mechanism of reconciling incremental learning and generalization. In Section 4, we apply Formal Concept Analysis (Ganter and Wille, 1996) to our network model. This analysis shows that the two neuron groups in the SLI network bear the extensional and intensional representations, respectively. There are other incremental learning models using two or more subnets (Norman and O'Reilly, 2003). For example, subnets for long-term and short-term memories are well-known (Kobayashi et al., 2001). These models need an artificial mechanism different from the network itself for regulating the relationship between subnets. The mechanism is not a simple inter-connection between subnets and is not physiologically intrinsic. Regulatory processes outside of a neural network itself are not appropriate solutions for understanding incremental learning in neural networks. In contrast, the proposed model does not need, except for lateral inhibitions, a special mechanism for differentiation and mediation between subnets. Moreover, there are almost no models which focus on differentiation and mediation between extensional and intentional representations (Gunji et al., 2006). These are discussed in more detail in Section 5.

2. Model

This section presents the activation algorithm and the learning algorithm of our proposed model. The activation algorithm includes two types of lateral inhibitions: GLI and SLI.

2.1. Activation algorithm

The proposed network model (Fig. 2(a)) is a multilayered neural network consisting of an input, an output and a number of nodes in a middle layer with lateral inhibitions. For an input ($0 < x < 1$), the activities in the middle layer ($0 < h_i < 1, i = 1, \ldots, M, M$ is the number of nodes in the middle layer) and the output ($0 < y < 1$) are given by:

$$g_i = pulse\,(x - c_i) \tag{1}$$

$$h_i = inhibit\,(g_i;\ g_1, \ldots, g_M) \tag{2}$$

$$y = sigmoid\,(\,\Sigma w_i \cdot h_i) \tag{3}$$

where c_i and w_i are parameters which are adjusted by learning. g_i is the activity in the middle layer which will be inhibited. The *inhibit* function will be described later. The *pulse* function and the *sigmoid* function are defined by:

$$pulse\,(u) = \frac{1}{(1 + \exp(-\alpha \cdot (u + d)))} - \frac{1}{(1 + \exp(-\alpha \cdot (u - d)))} \tag{4}$$

$$sigmoid\,(s) = \frac{1}{(1 + \exp(-\beta \cdot (s - \theta)))} \tag{5}$$

The right-hand of Eq. (5) is the conventional sigmoid function (we set $\beta = 4.0$ and $\theta = 0.5$). The right-hand of Eq. (4) is a linear combination of two sigmoid functions, one of which is positive (excitatory), and the other is negative (inhibitory). In Eq. (4), α and d are parameters which determine the range of the receptive field (we set $\alpha = 32$ and $d = 0.1$). The *pulse* function has a maximal value when $u = 0$, that is, $x - c_i = 0$. Neurophysiologically, the value is determined by balancing excitatory and inhibitory connections. In our proposed model, the parameter c_i is responsible for the balancing.

2.2. Global lateral inhibition and structural lateral inhibition

In Eq. (2), the *inhibit* function represents lateral inhibitions in the middle layer. As shown in Fig. 2(b), we propose two types of lateral inhibitions. The first is defined by:

$$inhibit\,(g_i; g_1, \ldots, g_M) = \begin{cases} 0, & if \quad g_{i\_\max} - g_i \leq EM, i \neq i\_\max \\ g_i, & \qquad else \end{cases} \tag{6}$$

where *i_max* is the index of the node whose activity is higher than others (the index of the winner node), g_{i_max} is the activity of the node. We call lateral inhibitions defined by Eq. (6) *global lateral inhibition* (GLI). We call the activation algorithm defined by Eqs. (1)–(6) GLI, too. We introduce GLI in order to show the trade-off between the generalization ability and the incremental learning