
Learning to learn with backpropagation of Hebbian plasticity

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Abstract

Hebbian plasticity is a powerful principle that allows biological brains to learn from their lifetime experience. By contrast, artificial neural networks trained with backpropagation generally have fixed connection weights that do not change once training is complete. While recent methods can endow neural networks with long-term memories, Hebbian plasticity is currently not amenable to gradient descent. Here we derive analytical expressions for the gradients for neural networks with Hebbian plastic connections. Using these expressions, we can use backpropagation to train not just the baseline weights of the connections, but also their plasticity. As a result, the networks "learn how to learn" in order to solve the problem at hand: the trained networks automatically perform fast learning of unpredictable environmental features during their lifetime, expanding the range of solvable problems. We test the algorithm on simple tasks including pattern completion, one-shot learning, and reversal learning. In each case, the algorithm successfully learns how to learn the relevant associations from short (one-shot) instruction. We conclude that backpropagation of Hebbian plasticity offers a powerful model for lifelong learning.

1 Introduction

Living organisms endowed with neural systems exhibit remarkably complex behaviors. While much of this complexity results from evolutionary learning over millions of years, it also results from the ability of neural systems to learn from experience during their lifetime. Indeed, this ability for lifelong learning is itself a product of evolution, which has fashioned not just the overall connectivity of the brain, but also the plasticity of these connections.

Lifetime learning is beneficial for several reasons. For one thing, some environmental features can simply not be predicted at birth and/or change over time (e.g. the position of food sources, the identifying features of other individuals for social species, etc.), requiring learning from experience in contact with the environment. Furthermore, even for predictable environmental features, much of the information necessary to produce adaptive behavior can be obtained "for free" by learning from the environment, thus removing a potentially huge chunk of the search space that evolution must explore. For example, the connectivity of primary visual cortex is fashioned by Hebbian plasticity rather than having each single connection genetically specified, allowing a huge number of cells to organize into a powerful, reliable information-processing system with minimal genetic specification.

Lifetime long-term learning in living brains generally follows the Hebbian principle: a cell that consistently contributes in making another cell fire will build a stronger connection to that cell. Note that this generic principle can be implemented in many different ways, including covariance learning, instar and outstar rules, BCM learning, etc. (see [5] and references therein).

Backpropagation methods can train neural networks to perform remarkably complex tasks. However, they are generally applied to fixed-weights networks. Several methods have been proposed to make lifelong learning amenable to backpropagation, including most recently neural Turing machines [1, 2] and memory networks [4]. However, it would be useful to incorporate the powerful, well-studied principle of Hebbian plasticity in backpropagation training.

Here we show that neural networks with Hebbian plastic synapses can be optimized by gradient descent and backpropagation. To this end, we derive analytic expressions for the gradients of neural responses over weights and plasticity parameters. Finally, we use these gradients to train neural networks for simple tasks, including one-shot and reversal learning, showing that the resulting networks successfully learn from experience.

All software used for the present paper is available at <http://github.com/thomasmiconi>.

2 Networks with Hebbian synapses

We consider networks where the strength of each connection can vary according to Hebbian plasticity over the course of the network’s lifetime. We will arrange things so that each network is fully specified by fixed parameters which determine both the baseline weight *and* the degree of plasticity of each connection. After training, these parameters are fixed and unchanging over the network’s lifetime, but govern the way in which each connection changes over time, as a result of experience, according to Hebbian plasticity.

We want to apply backpropagation to optimize these networks parameters. Therefore, our goal is to find expressions for the gradient of the response of any given cell, over the weights and plasticity parameters of its incoming connections.

Crucially, note that these gradients will take a time-dependent form: when Hebbian plasticity is present, the activity of a cell at a given time can influence its future responses, even in the absence of recurrent connections, due to its Hebbian effect on long-term connection strengths.

To model Hebbian plasticity, we maintain a time-dependent quantity for each connection in the network, which we call the *Hebbian trace* for this connection. In this paper, we use the simplest stable form of Hebbian trace, namely, the running average of the product of pre- and post-synaptic activities. Thus, for a given target cell, the Hebbian trace associated with its k -th incoming connection is defined as follows:

$$Hebb_k(t) = (1 - \gamma) * Hebb_k(t - 1) + \gamma * x_k(t) * y(t) \quad (1)$$

where $y(t)$ is the activity of the post-synaptic cell, $x_k(t)$ is the activity of the pre-synaptic cell, and γ is a time constant. While other expressions of Hebbian plasticity are possible, this simple form turns out to be adequate for our present purposes and simplifies the mathematics.

The Hebbian trace is maintained automatically, independently of network parameters, for each connection. Given this Hebbian trace, the actual strength of the connection at time t is determined by two fixed parameters: a fixed weight w_k , which determines the “baseline”, unchanging component of the connection; and a *plasticity parameter* α_k , which specifies how much the Hebbian trace influences the actual connection. More formally, the response y of a given cell can be written as a function of its inputs as follows:

$$y(t) = \tanh \left\{ \sum_{k \in \text{inputs}} [w_k x_k(t) + \alpha_k Hebb_k(t) x_k(t)] + b \right\} \quad (2)$$

Where b is a bias parameter.

3 Gradients

In order to use backpropagation, we must find the gradient of y over the w_k and α_k parameters. As mentioned above, these gradients will necessarily involve activities at previous times. Fortunately, these gradients turn out to have a simple, recursive form.

Temporarily omitting the tanh nonlinearity (see below), we get the following expressions:

$$\frac{\partial y(t_z)}{\partial w_k} = x_k(t_z) + \sum_{l \in \text{inputs}} [\alpha_l x_l(t_z) \sum_{t_u < t_z} (1 - \gamma) \gamma^{t_z - t_u} x_l(t_u) \frac{\partial y(t_u)}{\partial w_k}] \quad (3)$$

$$\frac{\partial y(t_z)}{\partial \alpha_k} = x_k(t_z) \text{Hebb}_k(t_z) + \sum_{l \in \text{inputs}} [\alpha_l x_l(t_z) \sum_{t_u < t_z} (1 - \gamma) \gamma^{t_z - t_u} x_l(t_u) \frac{\partial y(t_u)}{\partial \alpha_k}] \quad (4)$$

(See Appendix for a full derivation.)

These equations express the gradient of $y(t_z)$ as a function of the gradients of $y(t_z < t_u)$, that is, recursively.

In each of these equations, the summand over previous times $t_u < t_z$ is essentially the partial derivative of the Hebbian traces at time t_z with respect to either w_k (Eq. 3) or α_k (Eq. 4). Since the Hebbian trace is the exponential average of previous products of x and y , these partial derivatives turn out to be sums of the previous gradients of y over the corresponding parameter, multiplied by the concomitant activity of the input cell x_k (the γ terms account for the exponential decay of the running average). Thus, the gradient at time t_z is a function of (the weighted sum of) the gradients at times $t_u < t_z$.

Note that the sum is over the Hebbian traces of *all* inputs to y , not just the one associated with connection k for which we are computing the gradient. This is because the values of w_k and α_k , by affecting y , also influence the Hebbian traces of all other connections to y - which will in turn further affect y at later times. This effect must be accounted for in the above gradients.

The above expression omits the tanh nonlinearity: it really provides the gradient of the expression within the curly braces in Eq. 2, that is, the “raw” output (call it y_{raw}) provided by incoming excitation and biases. To obtain the full gradient $\frac{\partial y(t_z)}{\partial w_k}$, we simply rewrite y as $y = \tanh(y_{raw})$ and apply the chain rule: $\frac{\partial y}{\partial w_k} = \frac{\partial \tanh(y_{raw})}{\partial y_{raw}} \frac{\partial y_{raw}}{\partial w_k} = (1 - y^2) \frac{\partial y_{raw}}{\partial w_k}$, where $\frac{\partial y_{raw}}{\partial w_k}$ is provided by Eq. 3 above (and similarly for $\frac{\partial y_{raw}}{\partial \alpha_k}$).

4 Experiments

4.1 Applying BOHP

In all tasks described below, lifetime experience is divided into *episodes*, each of which lasts for a certain number of timesteps. At the beginning of each episode, all Hebbian traces are initialized (set to 0). Then, at each timestep, the network processes an input pattern and produces an output according to its current parameters, and the Hebbian traces are updated according to Equation 1. Furthermore, errors and gradients are also computed. At the end of each episode, the errors and gradients at each timestep are used to update network parameters (weights and plasticity coefficients) according to error backpropagation and gradient descent. The whole process iterates until training completes.

4.2 Pattern completion

To test the BOHP method, we first apply it to a task for which Hebbian learning is known to be efficient, namely, pattern completion. The network is composed of an input and an output layer, each having N neurons. In every episode, the network is first exposed to a random binary vector of length N with at least one nonzero element. This binary vector represents the pattern to be learned. Then, at the next timestep, a partial pattern containing only one of the non-zero bits of the pattern (all other bits set to 0) is presented. The task of the network is to produce the full pattern in the output layer. The error for each episode is the Manhattan distance between the network’s output at the second time step and the full pattern (network response during the first step is ignored).

The algorithm quickly and reliably learns to solve the task (Figure 1). The final networks after training exhibit the expected pattern: each input node sends one strong, fixed connection to the corresponding output node, as well as one plastic connection to every output node. As a result, during

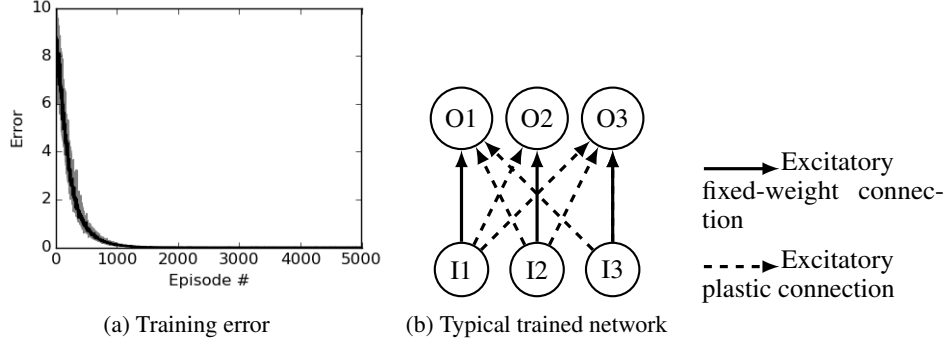


Figure 1: Results for the pattern completion experiment. (a) Mean absolute error per timestep over each episode, for mutually exclusive stimuli. The dark line indicates median error over 20 runs, while shaded areas indicate interquartile range. For the last 500 episodes, training is halted and parameters are frozen. (b) Schema of a typical network after training. Only 3 elements shown for clarity (actual pattern size: 8 elements).

pattern presentation, each non-zero input develops a strong connection to every non-zero output due to Hebbian learning, ensuring successful pattern completion on the second step when one of the nonzero inputs is stimulated.

4.3 One-shot learning of arbitrary patterns

In this task, at each episode, the network must learn to associate each of two random binary vectors with its label. The labels are simply two-element vectors set to 01 for one of the vectors, and 10 for the other. Importantly, learning is one-shot: at the first timestep, the input consists of the first pattern, suffixed with label 01; and at the second timestep, the input vector is the second pattern, suffixed with label 10. These are the only times the labels are presented as inputs: at all other times, the input is one of the patterns, suffixed with the neutral suffix 00, and the network’s output must be the label associated with the current pattern.

The networks have an input layer ($N + 2$ nodes), a hidden layer (2 nodes), and an output layer (2 nodes). For simplicity, only the first layer of weights (input-to-hidden) can have plasticity. The final layer implements softmax competition between the nodes. Each episode lasts 20 timestep, of which only the first two contain the expected label for each pattern. We use cross-entropy loss between the output values and the expected label at each time step, except for the 2-step learning period during which network output is ignored.

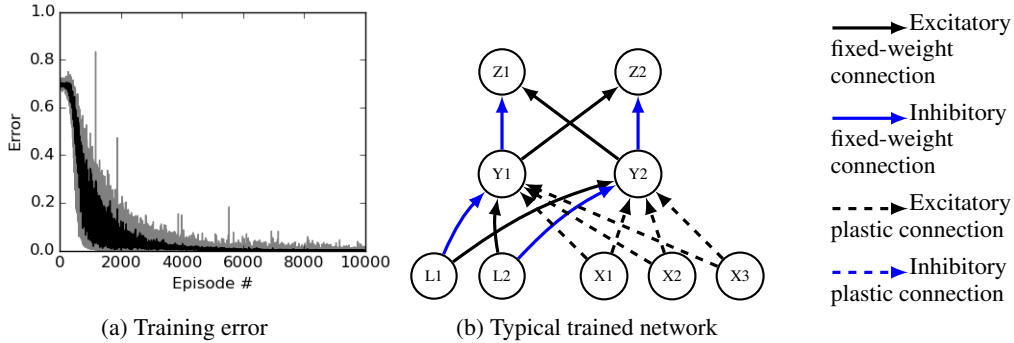


Figure 2: Results for the one-shot learning experiment. (a) Median absolute error per timestep over each episode. Conventions are as in Figure 1. (b) Schema of a typical network after training. In addition to the label nodes L1 and L2, only 3 pattern elements shown for clarity (actual pattern size: 8 elements). See text for details.

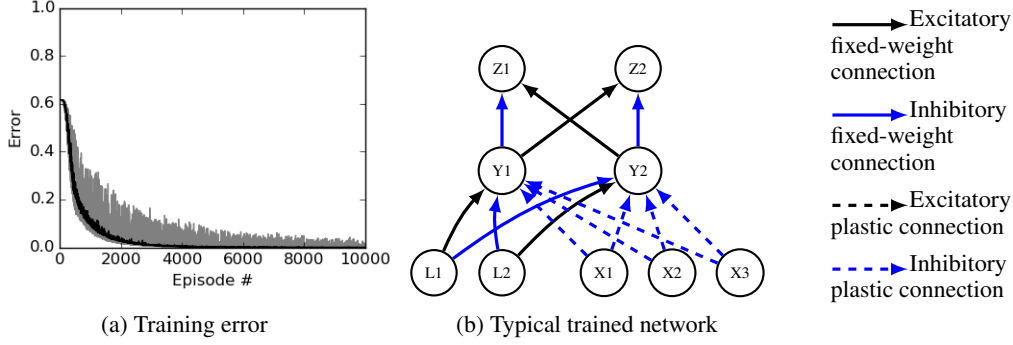


Figure 3: Results for the reversal learning experiment. Conventions are as in Figure 1. (a) Mean absolute error per timestep over each episode. (b) Schema of a typical network after training. Notice the negative plasticity connections from the pattern nodes to the hidden layer. See text for details.

Again, the algorithm reliably learns to solve the task (Figure 2). The trained networks are organized in such a way that one hidden node learns the pattern with label 01, and the other learns the pattern associated with label 10: they receive strong, fixed (positive and negative) connections from the label bits, but receive only strong plastic connections (with zero fixed-weight connections) from the pattern bit. This allows each node to be imprinted to the corresponding pattern. The weights between hidden and top layer ensures that the top two nodes produce the adequate label.

Note that some networks displayed a somewhat different pattern where all connections between pattern nodes and hidden nodes has negative plasticity coefficients. See below

4.4 Reversal learning

Previous experiments show that the algorithm can train networks to learn fast associations of environmental inputs. But can it also teach networks to adapt to a changing environment - that is, to perform continual learning over their lifetime?

To test this, we adapt the previous one-shot learning task into a continual learning task: halfway through each episode, we invert the two patterns, so that the pattern previously associated with label 01 is now associated with label 10, and vice-versa. We show each of the pattern with its updated label once. Then we resume showing input patterns with neutral, 00 suffixes, and expect the network's output to be the adequate new label for each input pattern.

The algorithm also successfully learns to solve this problem (Figure 3). The networks are somewhat similar to the ones obtained in one-shot learning, but with an important difference: connections from pattern input to hidden nodes now consistently have *negative* plasticity. While some networks trained for the one-shot learning task also had this feature, all networks trained for reversal learning consistently show it. This seems to be a crucial feature for reversal learning, because clipping plasticity coefficients to positive values prevents learning in this task while still allowing successful learning in the one-shot task (data not shown). What is the cause of this requirement for negative plasticity?

Negative plasticity implies that hidden layer firing will be anti-correlated to the presence of the imprinted stimulus. This in itself is unlikely to have any effect, since the effect can be negated by switching signs in the output layer. However, negative plasticity also has the important consequence of making the Hebbian traces *decrease* over time, rather than increase as they would if plasticity coefficient were positive.

It is well-known that Hebbian plasticity creates a positive feedback: correlation between input and output increases the connection weight, which in turn increases the correlation in firing, etc. This would pose a problem for one-shot reversal learning, because by the time the new patterns are shown, the existing associations would be too strong to be erased in a single timestep. However, with negative plasticity coefficients, the opposite is true: the large Hebbian trace created on initial imprinting becomes self-decreasing due to a *negative* feedback loop. As a result, the Hebbian traces created by the first association decrease over time. This has little effect on ongoing outputs, since

the output nonlinearities will magnify even small differences to produce the correct responses; for the same reason, one-shot learning (in which there is no reversal) is mostly indifferent to the sign of plasticity coefficients, since the episodes are short enough that the final Hebbian traces will always be large enough to support correct choice. However, in the case of reversal learning, decreasing Hebbian traces are vital: when the second association is shown, the existing Hebbian traces are now small enough to be completely erased (and indeed reversed) in a single presentation, which would not be the case under positive plasticity and increasing Hebbian traces.

In short, the BOHP method has not only determined which connections must be plastic to learn an association; it can also develop a precise fine-tuning of the temporal dynamics of this plasticity, by modulating the sign of plasticity coefficients. This remarkable result confirms the potential of BOHP to deal with temporal dynamics in environmental learning.

5 Conclusions and future work

In this paper we have introduced a method for designing networks endowed with Hebbian plasticity through gradient descent and backpropagation. This method allows the network to “learn how to learn” in order to solve a problem with unpredictable parameters. The method successfully solved simple learning tasks, including one-shot and reversal learning.

In this expository we only use a very simple form of Hebbian plasticity, namely, the running average of the product between pre- and post-synaptic activities. However, there are other possible formulations of Hebbian plasticity, such as covariance learning (mean-centering pre- and post-synaptic responses), instar and outstar rules, or BCM learning. These can be implemented in BOHP by rewriting the gradient equations appropriately, which might expand the capacities of BOHP. However, as shown above, the simple Hebbian plasticity used here can already produce fast, reliable lifelong learning.

Furthermore, the networks shown here use fixed plasticity constants to determine the strength of plasticity. However, in biological brains, plasticity is modulated over time by various neuromodulators (especially dopamine, acetylcholine and norepinephrine), which are themselves under neural control. Thus, biological brains can decide not just where, but *when* to apply plasticity, which is crucial for learning complex behaviors. While neuromodulation has been used in neural networks built by evolutionary methods [3], the methods described in this paper could be extended to allow backpropagation to design modutable-plasticity networks.

In addition, while we used very simple networks with only one plastic layer, the gradients derived here can potentially be applied to more complex networks, including large multi-layer networks and recurrent networks. We are currently exploring the application of BOHP to larger networks for more complex tasks.

In conclusion, we suggest that backpropagation of Hebbian plasticity is an efficient way to endow neural networks with long-term memories and lifelong learning abilities.

Appendix

Here we provide a derivation of the gradients of output cell response y at a given timestep t_z with regard to the α coefficient of an incoming connection k (where input activity of the pre-synaptic neuron at this connection is denoted by x_k).

First we simply write out the full expression for y , from Equation 2 (again, we initially omit the tanh nonlinearity):

$$\frac{\partial y(t_z)}{\partial \alpha_k} = \frac{\partial}{\partial \alpha_k} \left[\sum_{l \in \text{inputs}} w_l x_l(t_z) + \sum_{l \in \text{inputs}} \alpha_l \text{Hebb}_l(t_z) x_l(t_z) \right]$$

The first summand on the right-hand side denotes the inputs to y from incoming connections through the fixed weights; since this term does not depend on α in any way, we can remove it from the gradient computation.

The second summand denotes inputs through plastic connections. The cases for $l = k$ and $l \neq k$ must be handled differently, since we are differentiating with regard to α_k :

$$\frac{\partial y(t_z)}{\partial \alpha_k} = \frac{\partial}{\partial \alpha_k} \left[\sum_{l \neq k} \alpha_l \text{Hebb}_l(t_z) x_l(t_z) + \alpha_k \text{Hebb}_k(t_z) x_k(t_z) \right] \quad (5)$$

$$= \sum_{l \neq k} \left[\frac{\partial}{\partial \alpha_k} (\alpha_l x_l(t_z) \text{Hebb}_l(t_z)) \right] + \frac{\partial}{\partial \alpha_k} [\alpha_k \text{Hebb}_k(t_z) x_k(t_z)] \quad (6)$$

With regard to α_k , the derivative in the first right-hand-side term has the form $d(\text{Const} * f(\alpha_k))/d\alpha_k$, since only the $\text{Hebb}_l(t_z)$ depends on α_k (indirectly through y). By contrast, the second right-hand-side term has the form $d(\text{Const} * \alpha_k * f(\alpha_k))/d\alpha_k$, so we must develop it using the identity $(xf(x))' = xf'(x) + f(x)$. Therefore:

$$\frac{\partial y(t_z)}{\partial \alpha_k} = \sum_{l \neq k} [\alpha_l x_l(t_z) \frac{\partial}{\partial \alpha_k} \text{Hebb}_l(t_z)] + x_k(t_z) (\alpha_k \frac{\partial}{\partial \alpha_k} \text{Hebb}_k(t_z) + \text{Hebb}_k(t_z))$$

Replacing the $\text{Hebb}(t)$ terms by their full expression as the accumulated product of x and y (Eq. 1), we get:

$$\begin{aligned} \frac{\partial y(t_z)}{\partial \alpha_k} &= \sum_{l \neq k} [\alpha_l x_l(t_z) \frac{\partial}{\partial \alpha_k} \sum_{t_u < t_z} (1 - \gamma) \gamma^{t_z - t_u} x_l(t_u) y(t_u)] \\ &\quad + x_k(t_z) [\alpha_k \frac{\partial}{\partial \alpha_k} \sum_{t_u < t_z} (1 - \gamma) \gamma^{t_z - t_u} x_k(t_u) y(t_u) + \text{Hebb}_k(t_z)] \end{aligned} \quad (7)$$

$$\begin{aligned} &= \sum_{l \neq k} [\alpha_l x_l(t_z) \sum_{t_u < t_z} (1 - \gamma) \gamma^{t_z - t_u} x_l(t_u) \frac{\partial}{\partial \alpha_k} y(t_u)] \\ &\quad + x_k(t_z) [\alpha_k \sum_{t_u < t_z} x_k(t_u) (1 - \gamma) \gamma^{t_z - t_u} \frac{\partial}{\partial \alpha_k} y(t_u) + \text{Hebb}_k(t_z)] \end{aligned} \quad (8)$$

$$= \sum_{l \in \text{inputs}} [\alpha_l x_l(t_z) \sum_{t_u < t_z} (1 - \gamma) \gamma^{t_z - t_u} x_l(t_u) \frac{\partial}{\partial \alpha_k} y(t_u)] + x_k(t_z) \text{Hebb}_k(t_z) \quad (9)$$

where in the last equation above, l runs over all incoming connections to y , including k . This recursive gradient equation is identical to Eq. 4.

Eq. 3 is derived much in the same manner (though slightly simpler since we do not need to use the $(xf(x))' = xf'(x) + f(x)$ identity). For future applications to many-layers networks, equations for the gradient $\frac{\partial y(t_z)}{\partial x_k}$ are easily obtained with a similar derivation.

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