Improved multitask learning through synaptic intelligence

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Abstract
Deep learning has led to remarkable advances when applied to problems where the data distribution does not change over the course of learning. In stark contrast, biological neural networks continually adapt to changing domains, and solve a diversity of tasks simultaneously. Furthermore, synapses in biological neurons are not simply real-valued scalars, but possess complex molecular machinery enabling non-trivial learning dynamics. In this study, we take a first step toward bringing this biological complexity into artificial neural networks. We introduce a model of intelligent synapses that accumulate task relevant information over time, and exploit this information to efficiently consolidate memories of old tasks to protect them from being overwritten as new tasks are learned. We apply our framework to learning sequences of related classification problems, and show that it dramatically reduces catastrophic forgetting while maintaining computational efficiency.

1. Introduction
Artificial neural networks (ANNs) have become an indispensable asset for applied machine learning and rival human performance in a variety of domain specific tasks (LeCun et al., 2015). Although originally inspired by biology (Fukushima & Miyake, 1982), the underlying design principles and learning methods differ substantially from biological neural networks. For instance, parameters of ANNs are learned on a dataset in the training phase, and then frozen and used statically on new data in the deployment or recall phase. To accommodate changes in the data distribution, ANNs typically have to be re-trained on the entire dataset to avoid overfitting and catastrophic forgetting (Choy et al., 2006; Goodfellow et al., 2013).

On the other hand, biological neural networks exhibit continual learning in which they acquire new knowledge over a lifetime. It is therefore difficult to draw a clear line between a learning and recall phase. Somehow, our brains have evolved to learn from non-stationary data and to update internal memories or beliefs on-the-fly. While it is unknown how this feat is accomplished in the brain, it seems likely that the unparalleled biological performance in continual learning problems relies on specific features implemented by the underlying biological wetware that are not reflected in current ANNs.

Perhaps one of the greatest gaps in the design of modern ANNs and biological networks lies in the complexity of synapses. In ANNs, individual synapses (weights) are typically described by a single scalar quantity. On the other hand, individual biological synapses are complex dynamical systems. Chemical synapses, the most abundant synapse in the brain, make use of molecular machinery that endows them with a potentially high-dimensional state space that can affect plasticity at different spatial and temporal scales (Redondo & Morris, 2011). While this complexity has been surmised to serve memory consolidation (Fusi et al., 2005; Lahiri & Ganguli, 2013; Benna & Fusi, 2016), few studies have illustrated how the added synaptic complexity benefits learning in neural network models in a supervised setting across multiple tasks.

Here we undertake such a study. Specifically, we study the role of internal synaptic dynamics to enable ANNs to learn to solve sequences of classification tasks. While simple, scalar one-dimensional synapses suffer from “catastrophic forgetting”, in which the network “forgets” previously learnt tasks when trained on a novel task, this problem can be largely alleviated by complex synapses with a three-dimensional state space. In our model, the synaptic state tracks the past and current parameter value, and maintains an online-estimate of the synapse’s “importance” toward solving problems encountered in the past. Our importance measure can be computed locally at each synapse during training, and represents the local contribution of each synapse to the change in the global loss. We evaluate our approach on sequential learning tasks, and show that ANNs endowed with complex synapses enjoy significantly improved performance. Finally, we discuss the relation of our approach to diagonal estimates of the Hessian, as well as the Fisher information metric, which underlies an
2. Prior work

The problem of alleviating catastrophic forgetting has been addressed in many previous studies. These studies can be broadly partitioned into (1) architectural, (2) functional, and (3) structural approaches.

Architectural approaches to catastrophic forgetting alter the architecture of the network to reduce interference between tasks without altering the objective function. The simplest form of architectural regularization is freezing certain weights in the network so that they stay exactly the same (Razavian et al., 2014). A slightly more relaxed approach reduces the learning rate for layers shared with the original task while fine-tuning to avoid dramatic changes in the parameters (Donahue et al., 2014; Yosinski et al., 2014). More advanced approaches using different nonlinearities like ReLU, MaxOut, and local winner-take-all have been shown to improve performance on permuted MNIST and sentiment analysis tasks in (Srivastava et al., 2013; Goodfellow et al., 2013). Moreover, injecting noise to sparsify gradients using dropout also improves performance (Goodfellow et al., 2013). Recent work from Rusu et al. (2016) proposed more dramatic architectural changes where the entire network for the previous task is copied, and augmented with new features while solving a new task. This entirely prevents forgetting on earlier tasks, but the architectural complexity grows with the number of tasks.

Functional approaches to catastrophic forgetting add a regularization term to the objective that penalizes changes in the input-output function of the neural network. In (Li & Hoiem, 2016), the log probabilities of data from the new task are encouraged to be near the log probabilities of the data from the old task, similar to (Hinton et al., 2014). Similarly, Jung et al. (2016) regularize the $\ell_2$ distance between the final hidden activations instead of the cross entropy of the log probabilities. Both of these approaches to regularization aim to preserve aspects of the input-output mapping for the old task, but require storing or computing additional activations using the old task’s parameters. This makes the functional approach to catastrophic forgetting computationally expensive as it requires computing a forward pass through the old task’s network for every new data point.

The third technique, structural regularization, involves penalties on the parameters to encourage them to stay close to the parameters for the old task. Recently, Kirkpatrick et al. (2016) proposed elastic weight consolidation (EWC), a quadratic penalty on the difference between the parameters for the new and old task. They used a diagonal weighting proportional to the diagonal of the Fisher information matrix over the old parameters on the old task. Exactly computing the diagonal of the Fisher requires summing over all possible output labels and thus has complexity linear in the number of outputs. This limits the application of this approach to low-dimensional output spaces.

3. Synaptic framework

To tackle the problem of continual learning in neural networks, we sought to build a simple online algorithm which could be implemented locally at each synapse. Specifically, we aim to endow each individual synapse with a local measure of “importance” in solving tasks the network has been trained on in the past. When training on a new task we penalize changes to important parameters to avoid old “memories” from being overwritten. To that end, we developed a class of algorithms which keep track of an importance measure $\omega_k^\mu$ which reflects past credit for improvements of the global objective $L_\mu$ for task $\mu$ to individual synapses or parameters $\theta_k$.
of successful training lies in finding learning trajectories for which the endpoint lies close to a minimum of the loss function $L$. Let us first consider the change in loss for an infinitesimal parameter update $\delta(t)$ at time $t$. In this case the change in loss is well approximated by the gradient $g = \frac{\partial L}{\partial \theta}$ and we can write

$$L(\theta(t) + \delta(t)) - L(\theta(t)) \approx \sum_k g_k(t) \delta_k(t), \quad (1)$$

which illustrates that each parameter change $\delta_k(t) = \theta_k'(t)$ contributes the amount $g_k(t)\delta_k(t)$ to the change in total loss.

To assign credit to an entire trajectory through parameter space we have to sum over all infinitesimal changes. This amounts to computing the path integral of the parameter trajectory over the gradient

$$\int_C g(\theta(t)) d\theta = \int_{t_0}^{t_1} g(\theta(t)) \cdot \theta'(t) dt. \quad (2)$$

Because the gradient is a conservative field, the value of the integral is equal to the difference in loss between end and starting points $L(\theta(t_1)) - L(\theta(t_0))$. Crucial to our approach, we can decompose Eq. 2 as a sum over the individual parameters

$$\int_{t_{\nu-1}}^{t_\nu} g(\theta(t)) \cdot \theta'(t) dt = \sum_k \int_{t_{\nu-1}}^{t_\nu} g_k(\theta(t)) \theta_k'(t) dt \equiv -\sum_k g_k(t) \theta_k(t), \quad (3)$$

The $\omega_k$ now have an intuitive interpretation as the parameter specific contribution to changes in the total loss. Note that we have introduced the minus sign in the second line, because we are typically interested in decreasing the loss.

In practice, we can approximate $\omega_k$ online as the running sum of the product of the gradient $g_k(t) = \frac{\partial L}{\partial \theta_k}$ with the parameter update $\theta_k'(t) = \frac{\partial L}{\partial \theta_k}$. While for batch gradient descent with an infinitesimal learning rate, $\omega_k$ can be directly interpreted as the per-parameter contribution to changes in the total loss, in most practical scenarios the true gradient is approximated by stochastic gradient descent (SGD). This approximation introduces noise into the estimate of $g_k$. As a direct consequence, the approximated $\omega_k$ will typically overestimate the true value of $\omega_k$.

How can the knowledge of $\omega_k$ be exploited to improve continual learning? The problem we are trying to solve is to minimize the total loss function $L = \sum_\mu L_\mu$, with the limitation that we do not have access to loss functions of tasks we were training on in the past. Instead, we only have access to the current loss function $L_\mu$ for task $\mu$ at any given time. To avoid catastrophic forgetting of all previous tasks $(\nu < \mu)$ while training task $\mu$, we want to avoid drastic changes to weights which were particularly influential in the past. These are precisely those synapses with large $\omega_k$ (cf. Eq. 3).

To avoid large changes to important parameters, we use a modified cost function $\tilde{L}_\mu$ which adds a squared $\ell_2$ penalty on parameter changes weighted by their importance. Specifically, we use

$$\tilde{L}_\mu = L_\mu + c \sum_k \omega_k^\mu (\tilde{\theta}_k - \theta_k)^2 \quad (4)$$

where we have introduced the dimensionless strength parameter $c$, the reference weight corresponding to the parameters at the end of the previous task $\tilde{\theta}_k = \theta_k(t_{\nu-1})$, and the per-parameter regularization strength:

$$\Omega_k^\mu = \sum_{\nu < \mu} \frac{\omega_k^\nu}{(\Delta_k^\nu)^2 + \xi}. \quad (5)$$

The term in the denominator $\Delta_k^\nu = \theta_k(t_\nu) - \theta_k(t_{\nu-1})$ ensures that the regularization term carries the same units as the loss $L$. Ensuring correctness of units also substantially reduces tuning of the hyperparameter $c$. We also introduce an additional dampening parameter, $\xi$, to bound the expression in cases where $\Delta_k^\nu \rightarrow 0$. Unless otherwise stated, the $\omega_k$ are updated continuously during training, whereas the cumulative importance measures, $\Omega_k^\mu$, and the reference weights, $\tilde{\theta}_k$ are only updated at the end of each task. After updating the $\Omega_k^\mu$, the $\omega_k$ are reset to zero.

Let us consider the example illustrated in Figure 1 in which we learn two tasks. We first train on Task 1. At time $t_1$ the parameters have approached a local minimum of the Task 1 loss $L_1$. But, the same parameter configuration is not close to a minimum for Task 2. Consequently, while training on Task 2 without any additional precautions, the $L_1$ loss may inadvertently increase (Fig. 1, black trajectory). However, when $\theta_2$ “remembers” that it was important to decreasing $L_1$, it can exploit this knowledge during training on Task 2 by staying close to its current value (Fig. 1, orange trajectory). While this will almost inevitably result in a decreased performance on Task 2, this decrease could be negligible, whereas the gain in performance on both tasks combined can be substantial.

The approach presented here is similar to EWC (Kirkpatrick et al., 2016) in that more influential parameters are pulled back stronger towards a reference weight with which good performance was achieved on previous tasks. However, in contrast to EWC, here we are putting forward a method which allows for online computation of the importance measure, whereas EWC relies on the diagonal of the Fisher information metric at the final parameters, which has to be computed during a separate phase at the end of each task.
4. Theoretical analysis of the path integral

Here we provide a simple theoretical underpinning for our approach by analyzing what the path integral in (3) for the parameter specific importance $\omega^w_k$ and its normalized version $\Omega^w_k$ in (5) actually computes in terms of the geometry of the error function in a simple situation. In particular, consider an error function corresponding to a quadratic bowl

$$E(\theta) = \frac{1}{2}(\theta - \theta^*)^T H(\theta - \theta^*),$$

with a minimum at $\theta^*$ and a Hessian matrix $H$. Further consider batch gradient descent dynamics on this error function. In the limit of small discrete time learning rates, this descent dynamics is described by the continuous time differential equation

$$\frac{d\theta}{dt} = -\frac{\partial E}{\partial \theta} = -H(\theta - \theta^*),$$

where $\tau$ is related to the learning rate. If we start from an initial condition $\theta(0)$ at time $t = 0$, an exact solution to the descent path is given by

$$\theta(t) = \theta^* + e^{-\frac{1}{\tau} H \frac{t}{\tau}}(\theta(0) - \theta^*),$$

yielding the time dependent update direction

$$\theta'(t) = \frac{d\theta}{dt} = -\frac{1}{\tau} H e^{-\frac{1}{\tau} H \frac{t}{\tau}}(\theta(0) - \theta^*).$$

Now, under gradient descent dynamics, the gradient obeys $\dot{g} = \frac{2\theta}{\tau}$, so the $\omega^w_k$ in (3) are computed as the diagonal elements of the matrix

$$Q = \tau \int_0^\infty dt \frac{d\theta}{dt} \frac{d\theta}{dt}^T.$$

An explicit formula for $Q$ can be given in terms of the eigenbasis of the Hessian $H$. In particular, let $\lambda^\alpha$ and $u^\alpha$ denote the eigenvalues and eigenvectors of $H$, and let $d^\alpha = u^\alpha \cdot (\theta(0) - \theta^*)$ be the projection of the discrepancy between initial and final parameters onto the $\alpha$th eigenvector. Then inserting (9) into (10), performing the change of basis to the eigenmodes of $H$, and doing the integral yields

$$Q_{ij} = \sum_{\alpha,\beta} u^\alpha_i d^\alpha \frac{\lambda^\alpha \lambda^\beta}{\lambda^\alpha + \lambda^\beta} d^\beta u^\beta_j.$$  

Note that as a time-integrated steady state quantity, $Q$ no longer depends on the time constant $\tau$ governing the speed of the descent path. At first glance, the $Q$ matrix elements depend in a complex manner on both the eigenvectors and eigenvalues of the Hessian, as well as the initial condition $\theta(0)$. To understand this dependence, let’s first consider averaging $Q$ over random initial conditions $\theta(0)$, such that the collection of discrepancies $d^\alpha$ constitute a set of zero mean iid random variables with variance $\sigma^2$. Thus we have the average $\langle d^\alpha d^\beta \rangle = \delta_{\alpha\beta} \sigma^2$. Performing this average over $Q$ then yields

$$Q_{ij} = \frac{1}{2} \sigma^2 \sum_{\alpha} u^\alpha_i \lambda^\alpha u^\beta_j = \frac{1}{2} \sigma^2 H_{ij}.$$  

Thus remarkably, after averaging over initial conditions, the $Q$ matrix, which is available simply by correlating parameter updates across pairs of synapses and integrating over time, reduces to the Hessian, up to a scale factor dictating the discrepancy between initial and final conditions. Indeed, this scale factor theoretically motivates the normalization in (5); the denominator in (5), at zero damping, $\xi$ averages to $\sigma^2$, thereby removing the scale factor $\sigma^2$ in (12).

However, we are interested in what $Q_{ij}$ computes for a single initial condition. There are two scenarios in which the simple relationship between $Q$ and the Hessian $H$ is preserved without averaging over initial conditions. First, consider the case when the Hessian is diagonal, so that $u^\alpha_i = \delta_{\alpha i} e_i$ where $e_i$ is the $i$th coordinate vector. Then $\alpha$ and $i$ indices are interchangeable and the eigenvalues of the Hessian are the diagonal elements of the Hessian: $\lambda^\alpha = H_{ii}$. Then (11) reduces to

$$Q_{ij} = \delta_{ij} (d^\alpha)^2 H_{ii}.$$  

Again the normalization in (5), at zero damping, removes the scale of movement in parameter space $(d^\alpha)^2$, and so the normalized $Q$ matrix becomes identical to the diagonal Hessian. In the second scenario, consider the extreme limit where the Hessian is rank 1 so that $\lambda^\alpha$ is the only nonzero eigenvalue. Then (11) reduces to

$$Q_{ij} = \frac{1}{2} (d^\alpha)^2 u^\alpha_i \lambda^\alpha u^\beta_j = \frac{1}{2} (d^\alpha)^2 H_{ij}.$$  

Thus again, the $Q$ matrix reduces to the Hessian, up to a scale factor which is corrected via normalization. The normalized importances then become the diagonal elements of the non-diagonal but low rank Hessian. We note that the low rank Hessian is the interesting case for multitask learning; low rank structure in the error function leaves many directions in synaptic weight space unconstrained by a given task, leaving open excess capacity for synaptic modification to solve future tasks without interfering with performance on an old task.

While we have analyzed the dynamics of batch gradient descent, in practice we will employ stochastic gradient descent via minibatches, which introduces noise in the gradient which can propagate through to the $Q$ matrix. However, at high SNR in the gradient estimate, which can be achieved via large minibatches or slow learning rates that
average over many gradient updates, we expect the theoretical results above to hold to good approximation.

Prior approaches toward measuring the sensitivity of parameters in a network have primarily focused on local metrics related to the curvature of the objective function at the final parameters (Martens, 2016). The Hessian is one possible metric, but it can be negative definite and computing even the diagonal adds additional overhead over standard backpropagation (Martens et al., 2012). An alternative choice is the Fisher information:

$$F = \mathbb{E}_{(x,y) \sim D, \theta \sim p_\theta(y|x)} \left[ \left( \frac{\partial \log p_\theta(y|x)}{\partial \theta} \right) \left( \frac{\partial \log p_\theta(y|x)}{\partial \theta} \right)^T \right]$$

(15)

While the Fisher information has a number of desirable properties (Pascual & Bengio, 2013), it requires computing gradients using labels sampled from the model distribution instead of the data distribution, and thus would require at least one additional backpropagation pass to compute online. For efficiency, the Fisher is often replaced with an approximation, the empirical Fisher (Martens, 2016), that uses labels sampled from the data distribution and can be computed directly from the gradient of the objective at the current parameters:

$$\bar{F} = \mathbb{E}_{(x,y) \sim D} \left[ \left( \frac{\partial \log p_\theta(y|x)}{\partial \theta} \right) \left( \frac{\partial \log p_\theta(y|x)}{\partial \theta} \right)^T \right]$$

(16)

$$\bar{F} = \mathbb{E}_{(x,y) \sim D} \left[ g(\theta)g(\theta)^T \right]$$

(17)

The diagonal of the empirical Fisher yields a very similar formula to our local importance measure $\omega$ in Eq. 3 under gradient descent dynamics. However, the empirical Fisher is computed at a single parameter value $\theta$ whereas the path integral is computed over a trajectory $\theta(t)$. This yields an important difference in the behavior of these metrics: for a quadratic the empirical Fisher at the minimum will be 0 while the path integral will be proportional to the diagonal of the Hessian. Thus the path integral based approach yields an efficient algorithm with no additional gradients required that still recovers a meaningful estimate of the curvature.

5. Experiments

We evaluated our approach for multitask learning on the split and permuted MNIST benchmarks.

5.1. Split MNIST

We first evaluated our algorithm on a split MNIST benchmark. For this benchmark we split the full MNIST training data set (LeCun et al., 1998) into 5 subsets of consecutive digits. The 5 tasks correspond to learning to distinguish between two consecutive digits from 0 to 10. We used a small multi-layer perceptron (MLP) with only two hidden layers consisting of 256 units each with ReLU nonlinearities, and a standard categorical cross-entropy loss function plus our consolidation cost term (with damping parameter $\xi = 1 \times 10^{-3}$). To avoid the complication of crosstalk between digits at the readout layer due to changes in the label distribution during training, we used a multi-head approach in which the categorical cross entropy loss at the readout layer was computed only for the digits present in the current task. Finally, we optimized our network using a minibatch size of 64 and trained for 10 epochs using the adaptive optimizer Adam (Kingma & Ba, 2014) ($\eta = 1 \times 10^{-3}$, $\beta_1 = 0.9$, $\beta_2 = 0.999$). In this benchmark the optimizer state was reset after training each task.

To evaluate the performance, we computed the average classification accuracy on all previous tasks as a function of number of tasks trained. We now compare this performance between networks in which we turn consolidation dynamics on ($c = 1$) against cases in which consolidation was off ($c = 0$). During training of the first task the consolidation penalty is zero for both cases because there is no past experience that synapses could be regularized against. When trained on the digits “2” and “3” (Task 2), both the model with and without consolidation show accuracies close to 1 on Task 2. However, on average the networks without synaptic consolidation show substantial loss in accuracy on Task 1 (Fig. 2). In contrast to that, networks with consolidation only undergo minor impairment with respect to accuracy on Task 1 and the average accuracy for both tasks stays close to 1. Similarly, when the network has seen all MNIST digits, on average, the accuracy on the first two tasks, corresponding to the first four digits, has dropped back to chance levels in the cases without consolidation whereas the model with consolidation only shows minor degradation in performance on these tasks (Fig. 2).

5.2. Permuted MNIST benchmark

In this benchmark, we randomly permute all MNIST pixels differently for each task. We trained a MLP with two hidden layers with 2000 ReLUs each and softmax loss. We used Adam with the same parameters as before. However, here we used $\xi = 0.1$ and the value for $c = 0.1$ was determined via a coarse grid search on a heldout validation set. The mini batch size was set to 256 and we trained for 20 epochs. In contrast to the split MNIST benchmark we obtained better results by maintaining the state of the Adam optimizer between tasks. The final test error was computed on data from the MNIST test set. Performance is measured as the ability of the network to solve all tasks it has been trained on.
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Figure 2. Mean classification accuracy for the split MNIST benchmark as a function of the number of tasks. The first five panels show classification accuracy on the five tasks consisting of two MNIST digits each as a function of number of consecutive tasks. The rightmost panel shows the average accuracy, which is computed as the average over task accuracies for past tasks $\nu$ with $\nu < \mu$ where $\mu$ is given by the number of tasks on the x-axis. Note that in this setup with multiple binary readout heads, an accuracy of 0.5 corresponds to chance level. Error bars correspond to SEM (n=10).

Figure 3. Classification accuracy on all tasks as a function of number of tasks. Blue: Training error, no consolidation. Green: Training error, with consolidation. Red: Same as the blue line, but showing the test error. Gray: Data points for EWC extracted and replotted from Kirkpatrick et al. (2016). The top panel is a zoom-in on the upper part of the graph. Dotted line: Initial training accuracy on a single task. Black arrow: Training accuracy of the same network when trained on all tasks simultaneously.

To establish a baseline for comparison we first trained a network without synaptic consolidation ($c = 0$) on all tasks sequentially. In this scenario the system exhibits catastrophic forgetting, i.e. it learns to solve the most recent task, but rapidly forgets about previous tasks (blue line, Fig. 3). In contrast to that, when enabling synaptic consolidation, with a sensible choice for $c > 0$, the same network retains high classification accuracy on Task 1 while being trained on 9 additional tasks (Fig. 3). Moreover, the network learns to solve all other tasks with high accuracy and performs only slightly worse than a network which had trained on all data simultaneously (Fig. 3). Finally, these results were consistent across training and validation error and comparable to the results reported with EWC.

6. Discussion

We have shown that the problem of catastrophic forgetting commonly encountered in multitask learning scenarios can be alleviated by allowing individual synapses to estimate their importance for solving tasks in the past. By introducing a regularization penalty for changes to the most important synapses, novel tasks can be learned with minimal interference to previously stored memories.

The regularization penalty is similar to EWC as recently introduced by Kirkpatrick et al. (2016). However, our approach computes the per-synapse consolidation strength in an online fashion and requires minimal overhead compared to normal backpropagation training. However, our theoretical analysis revealed surprising commonalities between these two approaches, which may explain why both approaches yielded similar performance on the permuted MNIST benchmark.

Our approach requires each synapse to accumulate task relevant information during training. Specifically, synapses
have to integrate the product of their respective updates \( \delta \) with their gradient. Additionally, each synapse keeps a record of its past parameter value, which again is similar to EWC. Thus in these frameworks, synapses have to be thought of as multi-dimensional objects rather than simple scalar quantities.

This conceptual shift from scalar-valued synapses to higher-dimensional dynamical entities which have the ability to actively influence their fate during training is a phenomenon found ubiquitously in neurobiology. Changes to biological synapses can be induced rapidly through diverse plasticity induction protocols. However, whether synaptic changes occur and whether they are made permanent or left to decay on a slower timescale, crucially depends on various factors which are normally not captured in machine learning paradigms. For instance, the induction of synaptic plasticity may depend on the history and the synaptic state of individual synapses (Montgomery & Madison, 2002). Moreover, recent synaptic changes may decay on the timescale of hours unless specific plasticity related chemical factors are released. These chemical factors are thought to encode the valence or novelty of a recent change (Redondo & Morris, 2011). Finally, recent synaptic changes can be reset by stereotypical neural activity, whereas older synaptic memories become increasingly insensitive to reversal (Zhou et al., 2003).

Here, we used synaptic complexity to tackle one specific problem encountered in multitask learning, the problem of catastrophic forgetting. However, this now opens the door to entirely new directions of research in which we mirror neurobiology to endow individual synapses with potentially complex dynamical properties, that can be exploited to intelligently control learning dynamics in neural networks. In essence, in machine learning, in addition to adding depth to our networks, we may need to add intelligence to our synapses.

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