Insect cyborgs: Bio-mimetic feature generators improve machine learning accuracy on limited data

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Abstract

Machine learning (ML) classifiers always benefit from more informative input features. We seek to auto-generate stronger feature sets in order to address the difficulty that ML methods often experience given limited training data. A wide range of biological neural nets (BNNs) excel at fast learning, implying that they are adept at extracting informative features. We can thus look to BNNs for possible tools to improve performance of ML methods in this low-data regime. The insect olfactory network, though simple, learns new odors very rapidly, by means of three key elements: A competitive inhibition layer (Antennal Lobe, AL); a high-dimensional sparse plastic layer (Mushroom Body, MB); and Hebbian updates of synaptic weights. In this work, we deploy a computational model of the insect AL-MB as an automatic feature generator, attached as a front-end pre-processor so that its Readout Neurons provide new features, derived from the original features, for use by standard ML classifiers. We find that these “insect cyborgs”, i.e. classifiers that are part-insect model and part-ML method, have significantly better performance than baseline ML methods alone on a vectorized MNIST dataset. Relative Test set accuracy improves by an average of 6% to 33% depending on baseline ML accuracy, while relative reduction in Test set error reaches more than 50% for higher baseline accuracy ML models. The two basic structures in the AL-MB, a competitive inhibition layer and a high-dimensional sparse layer, coupled with Hebbian plasticity, act as effective, automated feature generators that substantially improve ML classification in the test case we examine.

1 Introduction

Machine learning (ML) methods in general, and neural nets (NNs) with backprop in particular, have posted tremendous successes in recent years [1][2][3]. However, these methods, and NNs in particular, typically require large amounts of training data to attain high performance. This creates bottlenecks to deployment, and constrains the types of problems that can be addressed [4]. Thus it is desirable to improve ML methods’ ability to learn from small training sets. This limited-data constraint is typical of a large and important group of ML targets, including tasks that use medical, scientific, or field-collected data, and also artificial intelligence efforts focused on rapid learning.

In this work, we seek to improve the input feature space which an arbitrary ML method will use for training. In particular, we propose an architecture that can be bolted onto the front end of an ML method, and which automatically generates, from the existing feature set, a new set of strongly class-separating features to supplement (or even replace) the existing feature set.

Biological neural nets (BNNs) are able to learn rapidly, even from just one or two samples. On the assumption that rapid learning requires effective ways to separate classes given limited data, we may
look to BNNs for effective feature-generators [5]. One of the simplest BNNs that can learn is the insect olfactory network [6], containing the Antennal Lobe (AL) [7] and Mushroom Body (MB) [8], which can learn a new odor given only five exposures. This simple but effective feedforward network is built around three key elements that are ubiquitous in BNN designs: Competitive inhibition, high-dimensional sparse layers, and Hebbian update mechanisms. Specifically, the AL-MB network contains: (i) A pre-processing layer (the AL) built of units that competitively inhibit each other [9]; (ii) Projection, with sparse connectivity, up into and then down out of a sparsely-firing high-dimensional layer (the MB) [10, 11], where the dimension shift is typically 10x to 100x [12]; and (iii) Hebbian updates of plastic synaptic connections to train the system. Roughly speaking, the Hebbian rule is “fire together, wire together”, i.e. updates are proportional to the product of firing rates of the sending and receiving neurons, \( \Delta w_{ij} = \alpha f_i f_j \) [13, 14]. Synaptic connections are largely random [15]. A schematic is given in Figure 1.

MothNet is a computational model of the *Manduca sexta* moth AL-MB [16] that demonstrated very rapid learning of vectorized MNIST digits, with performance superior to standard ML methods in the 1 to 10 training sample regime [17]. That is, it was able to encode substantial class-relevant information from very few samples. But MothNet also appears to have limited capacity: Accuracy leveled off at about 80%, consistent with related results in [18] and the biological fact that a moth can only learn about 8 odors.

In this work we examine whether the MothNet architecture can usefully serve, not as a classifier itself, but rather as the first stage of a multi-stage network. Our goal is to harness its class-information encoding abilities to generate strong features that can improve performance of a main downstream classifier. In particular, we test the following hypotheses:

1. The AL-MB architecture has an intrinsic clustering ability, due specifically of the competitive inhibition layer and/or the sparse high-dimensional layer. That is, these structures have an inductive bias towards separating classes (just as convolutional neural nets have an inductive bias towards distinguishing visual data).

2. Despite its limitations, the trained AL-MB is an effective feature generator: Its Readout neurons contain class-separating information that will boost an arbitrary ML algorithm’s ability to classify test samples.

We test these hypotheses by combining MothNet with a downstream ML module, so that the Readouts of the trained AL-MB model feed into the ML module as additional features (from the ML perspective, the AL-MB acts as an automatic feature generator; from the biological perspective, the ML module stands in for the downstream processing in more complex BNNs). Our Test Case is a non-spatially-correlated, 85-feature, 10-class task derived from the downsampled, vectorized MNIST dataset (hereafter “vMNIST” to emphasize its vectorized, non-spatial, structure). We restrict training set size to \( N \leq 100 \) samples per class, so that the ML modules do not attain full accuracy on the task using the 85 features (pixels) alone.

We find evidence that these hypotheses are correct: The high-dimensional sparse layer and (to lesser extent) the competitive inhibition layer, in combination with a Hebbian update rule, significantly improved the abilities of ML methods (NN, SVM, and Nearest Neighbors) to classify the test set in all cases, and especially when \( N \leq 30 \) training samples per class. That is, the input pixel features contain class-separating information that is not being extracted by the ML methods. The MothNet module encodes this information in a form that is accessible to the ML methods. If the learning performance of BNNs is any guide, these layers are simple, general-purpose feature generators that can potentially improve performance of ML methods in tasks where training data is limited.

### 2 Experimental setup

To generate vMNIST, we downsampled and preprocessed the MNIST dataset [19, 20] to give samples with 85 pixels-as-features stripped of spatial information, as in [17]. We note that vMNIST is not the “MNIST dataset” considered in its usual context of a task with spatial structure and large pools of training data. Rather, here the MNIST data served as raw material for a generic non-spatial Test Case. vMNIST had the advantage that our baseline ML methods (Nearest Neighbors, SVM, and Neural Net) did not attain full accuracy at low \( N \). So it acted as a good test of whether the AL-MB can improve classification by ML methods.

\[ \text{See Acknowledgements} \]
Figure 1: Schematic of the Moth Olfactory Network. Input features feed 1-to-1 into a 85-unit layer with competitive all-to-all inhibition (the AL). The AL projects with sparse, random connectivity (about 15%) into a 2500-unit sparsely-firing layer (the MB, with 5% to 10% activity). The MB projects densely to the Readout Neurons. The AL is not plastic. The only plastic synaptic weights are those that enter or leave the MB (in our experiments, the bulk of updates occurred between the MB and Readout Neurons). Training updates are done by Hebbian rule ($\Delta w_{ij} = \alpha f_i f_j$) and unused connections decay towards 0, as in [17]. MothNet instances were generated by randomly assigning connectivity maps and synaptic weights according to template distributions.

Full wiring details of the AL-MB model are given in [16]. Full Matlab code for MothNet simulations and these cyborg experiments can be found at https://github.com/charlesDelahunt/PuttingABugInML.

Competitive inhibition in the moth AL works roughly as follows. Each neural unit in the AL receives input from one feature, and has two outputs: An inhibitory signal to other neural units in the AL, and an excitatory signal to the MB. Thus, each feature tries to dampen other features’ presence in the sample’s output signature from the AL.

Sparsity in the MB is of two types: First, the projections from the AL to the MB are non-dense ($\approx 15\%$ non-zero). Second, MB neurons fire sparsely, in the sense that only the strongest 5% to 10% of the total population are allowed to fire (through a mechanism of global inhibition).

All weights are non-negative, and are initialized randomly. Weight updates affect only MB→Readout connections (the AL is not plastic, and AL→MB learning rates are slow). Hebbian updates occur according to: $\Delta w_{ij} = \alpha f_i f_j$ (if $f_i f_j > 0$), and $\Delta w_{ij} = -\delta w_{ij}$ (if $f_i f_j = 0$).

Nearest-Neighbors and SVM used Matlab built-in functions as in [17]. The Neural Nets used Matlab’s NN toolbox, with one layer (more layers did not help) and as many hidden units as features (i.e. 85 or 95; more units did not help). MothNet instances were generated randomly from templates. All hyperparameter details can be found in the online codebase. We note that our goal was to see if the MothNet-generated features improved on the baseline accuracy of the ML methods, whatever that baseline was, and that we deliberately varied the baseline by restricting training data. So the exact ML method hyperparameters were not central, as long as they were reasonable.

We ran two sets of experiments:

**Cyborg vs baseline ML methods experiments**

The main experiments were structured as follows:
1. A random set of $N$ training samples per class were drawn from $\epsilon$MNIST.
2. The ML methods trained on these samples, to provide a baseline (switch $B$ in Fig 2).
3. MothNet was trained on these same samples, using time-evolved stochastic differential differential equation
simulations and Hebbian updates as in [17] (switch A in Fig 2).

4. The ML methods were then retrained from scratch, with the Readout Neuron outputs from the trained MothNet instance fed in as additional features (switches AB in Fig 2). These were the “insect cyborgs”.

5. Trained ML accuracy of the baselines and cyborgs were compared to assess the value of the AL-MB as a feature generator.

Relative importance of AL vs MB experiments
There are two key structural components in the AL-MB, the competitive inhibition layer (the AL) and projection into a high-dimensional sparse layer (the MB) with Hebbian synaptic updates. These two structures can be deployed separately or together. In particular, the (trainable) high-dimensional sparse layer can be deployed with or without the competitive inhibition layer. In order to assess the relative value of the competitive inhibition layer, mutant MothNets were generated from templates that had a “pass-through” AL, i.e. with uniform weights and no lateral inhibition (switch in Fig 2).

Steps 1 to 4 above were followed using these mutant MothNets (so step 4 corresponded to switches AB in Fig 2). The results from step (4) were then compared to those of full cyborgs.

3 Results
The trained MothNet learners, alone, attained a mean accuracy of 58% to 75% depending on number of samples per class N (black line, Fig 3). The ML baseline methods started at 10% to 30% accuracy (for N = 1 sample per class), caught up with MothNet at N = 15 to 20, and continued rising to 80% to 88% accuracy (depending on method) at N = 100, where we stopped our sweep. Baseline accuracy is marked by the lower colored circles in Fig 3. All reported means are over 13 runs per data point.

MothNet-ML cyborgs, i.e. networks in which the 10 Readouts of the trained MothNet were fed into the ML module as 10 additional features, showed consistently and significantly improved Test set performance versus their ML baselines, for all ML methods at all N. Cyborg accuracy is marked by the upper colored circles in Fig 3 and the raw gains in accuracy are marked by thick vertical bars. These gains were fairly consistent (by ML method) across all N.

Raw increases in accuracy due to cyborgs were fairly stable for all ML models. This led to two trends in terms of relative changes. Relative gains, i.e. as percentage of baseline, were highest at low N training samples per class. Average gains were 10% to 33% at N ≤ 10, and 6% to 10% for N > 10. Of the ML methods, the Neural Net cyborgs had the best performance and also showed the highest

Figure 2: Schematic of the various Learner configurations. Two switches created the various models. In the ordinary MothNet, input pixels passed through the AL (switch A), then the MB, and prediction was based on a log-likelihood over the Readout Neurons as in [17]. The ordinary (baseline) ML module accepted only input pixels as features (switch B). Two cyborg variants were tested: In the full cyborg, the Readouts of an ordinary trained MothNet are fed into the ML module as additional features (switches AB). In a mutant cyborg used to test the role of the AL, Readouts from a trained MothNet with disabled (pass-through, no lateral inhibition) AL fed into the ML module as additional features (switches AB).
percentage gains. Conversely, the relative reduction in Test set error, as a percentage of baseline, increased substantially as the baseline accuracy increased. Thus, MothNet cyborgs reduced Test set error by over 50% on the most accurate models, such as NNs with >80% baseline accuracy. See Fig 4.

Remarkably, adding a MothNet front-end improved ML accuracy even in cases where the ML module baseline already exceeded the accuracy ceiling of MothNet (∼75%), at \( N = 15 \) to 100 samples per class. This implies that the Readouts of MothNet contain valuable clustering information which ML methods are able to leverage more effectively than MothNet itself does.

Also somewhat remarkable is that stand-alone MothNet out-performed even the cyborgs at \( N \leq 5 \). That is, adding an ML classifier to MothNet actually reduced the amount of class-separating information extracted in this very-few-sample regime. Consistent with this, the highest gains by the NN-cyborg at \( N = 1, 2 \) came from using only the MothNet’s Readouts as features and ignoring the original feature pixels, an indication of the strong clustering abilities of the AL-MB architecture.

Figure 3: Trained accuracy of baseline ML and full cyborg classifiers, vs number of training samples per class. Trained MothNet accuracy is plotted as a black line. Baseline ML accuracies are shown as small circles. ML methods used were Nearest Neighbors, SVM, and Neural Nets. MothNet cyborg accuracies are shown as larger circles. The increase in accuracy is marked by thick vertical bars. In almost every case the cyborgs had significantly improved accuracy (5% to 33% relative increase), indicating that the AL-MB Readouts are information-rich. Stand-alone MothNet was still the strongest classifier given \( N \leq 5 \) samples per class, but the cyborgs overtook MothNet much earlier (at \( N = 7 \)) than did the baseline ML methods (at \( N = 15 \) to 20). Std Devs (\( \sigma \)) for each baseline method are given as solid dots near the x-axis (cyborg \( \sigma \)s were similar). The inset shows the raw gain (cyborg over baseline) in units of baseline \( \sigma \)s, a measure of significance. 13 runs per data point.

3.1 Relative contribution of the competitive inhibition layer

Cyborgs built from MothNets with a “pass-through” AL still showed significant improvement in accuracy over baseline ML methods. About a third of the time (summed across all ML methods) the improvements were as high or higher than for MothNets with normal ALs (see Fig 5). This suggests that the high-dimensional, trainable layer (the MB) was of primary importance. However, the gains
Figure 4: Effects on test set accuracy of cyborg over baseline ML, vs baseline ML accuracy. A: Relative gains in accuracy over ML baseline, due to cyborg (given as %). Dots show the mean relative gains due to cyborgs over baseline accuracies for ML methods (this is the size of the vertical red bars, relative to baselines, in Figure 3). B: Relative reduction in test set error due to cyborg (given as %). Because raw gains were steady across all baseline accuracies, the reductions in test set error were very high for ML models with high baseline accuracy. Neural Net cyborgs enjoyed the highest gains overall. SVMs saw the least overall benefit. 13 runs per data point.

of the cyborgs with pass-through ALs were usually lower, generally between 60% and 90% of the gains posted by cyborgs with normal ALs (see Fig 5). This indicates that the competitive inhibition of the AL layer added value in terms of generating strong features.

In terms of overall effect on downstream ML modules, a functioning AL enabled slightly better, more reliable gains: Averaged over all ML methods and all numbers of training samples $N$, a functioning AL gave mean raw increase in accuracy = 5.63%, standard error ($\sigma/\sqrt{N}$) = 0.38; while a pass-through AL gave mean raw increase in accuracy = 5.00%, standard error = 0.43. For NN cyborgs, the AL contributed 0% to 40% of the total improvement, averaging about 15% over all values $N$ (red bars in Fig 5). In addition, a functioning AL contributed a large benefit in certain regimes of various ML methods, eg delivering 30% to 40% of the benefit in NN cyborgs at $N = 2$ to 7.

4 Discussion

Strong, automatically-generated feature sets enhance the power of ML algorithms to extract structure from data. They are always desirable tools, but especially so when training data is limited. Many current applications of NNs have access to vast amounts of (eg internet-generated) training data. However, many other ML targets, such as tasks for which data must be manually collected in medical, scientific, or field settings, do not have this luxury. They require ways to extract maximum value from the limited available data. This large class of ML targets also includes Artificial Intelligence systems that seek adaptive and rapid learning skills. In this context, biological structures and mechanisms are potentially useful tools, given that BNNs excel at rapid learning.

Our experiments deployed an architecture based on a simple BNN, the moth olfactory network, to generate features to support ML classifiers. The three key elements of this network are novel in the context of engineered NNs, but are endemic in BNNs of all complexity levels: (i) a competitive inhibition layer; (ii) a high-dimensional sparse layer; and (iii) a Hebbian plasticity mechanism for weight updates in training. Our experiments indicate that these structures, as combined in the MothNet model of the insect olfactory network, create a highly effective feature generator whose Readout Neurons contain strong class-specific information.
Figure 5: The relative importance of the MB and AL, vs number of training samples per class. The bars plot the ratio of gains posted by mutant cyborgs to the gains of full cyborgs (as shown in Fig 4), for the three ML methods. The mutant cyborgs had a pass-through AL without competitive inhibition. This allowed a rough estimate of the AL’s relative importance via subtraction. Bars exceeding 100% indicate that the pass-through AL resulted in greater mean gains than did the normal AL. The most important structure appears to be the high-dimensional sparse layer, but the competitive inhibition layer contributes, for certain combinations of ML method and $N$, up to 40% of the total gain. NNs benefitted most from the competitive inhibition layer. 13 runs per data point.

In particular, using MothNet as a feature generator upstream of standard ML methods significantly and consistently improved their learning abilities on eMNIST. That is, information in the raw feature distributions relevant to classification was not extracted by the ML methods alone, and pre-processing by MothNet had the effect of making that information accessible to the downstream ML classifier. Raw increases in accuracy were fairly steady at around 5% to 8%. Thus, relative increase in accuracy averaged 10% to 33% given 10 or fewer training samples per class, and 6% to 10% given 15 to 100 samples per class, while the relative reduction in Test set error increased to 30% to 40% for models with higher baseline accuracy. These gains held even when baseline ML accuracy was much higher than maximum MothNet accuracy, implying that the information encoded by MothNet is distinct from that encoded by ML methods, and thus always adds value.

Another way to look at these gains is in savings on training data: For example, with 30 training samples per class, a MothNet - NN cyborg attains the same Test accuracy (79%) as a NN baseline attains with 100 training samples per class, a savings of over 3x. These savings in training data, seen in Fig 3, consistently ranged between 1.5x to 3x. If these accuracy gains and commensurate savings were to hold at higher numbers of training samples, the savings in data requirements would be substantial, an important benefit for many ML use-cases.

Not only can these structures be readily prepended as feature generators to arbitrary ML modules, as we did here, but they can perhaps also be inserted as layers into deep NNs. Indeed, this is what BNNs appear to do.

**Comparison of the MB to sparse autoencoders** The insect MB, i.e. projection into a high-dimensional sparse space, naturally brings to mind sparse autoencoders (SA) [21][22]. However, there are several differences, beyond the fact that MBs are not trying to match the identity function.

First, in SAs the goal is typically to detect lower-dimensional structures that carry the input data. Thus the sparse layers of SAs have fewer active neurons than the nominal dimension of the input. In the MB, the number of neurons increases manyfold (eg 30x), so that even with enforced sparsity...
the number of active MB neurons is much greater than the input dimension: In MothNet there are approximately 150 - 200 active neurons in the MB vs 85 input features. The functional effects are also different: In MNIST experiments in [22], a sparse layer with 100 active neurons (vs 784 input pixels, i.e. ratio 1:8) captured only very local features and was not effective for feeding into shallow neural nets (though it was useful for deeper nets). In our experiments, a ratio of 2:1 (i.e. 16x that of the SA) generated features that were very effective as input to a shallow net.

Second, there is no off-line training or pre-tuning step, as used in some SAs, though of course Mother Nature has been tinkering with this system for a long time. Third, SAs typically (to our knowledge) require large amounts of training data (eg 5000 per class in [22]), while the MB needs as few as one training sample per class to bake in structure that improves classification. Fourth, the updates in SAs are by backprop, while those in MBs are Hebbian. While the ramifications of this difference are unclear, we suspect that the two methods yield distinct results, and that the dissimilarity of the optimizers (MothNet vs ML) was an asset in our experiments.

The MB shares with Reservoir Networks [23] a (non-linear) projection into a high-dimensional space and (linear) projection out to a Readout layer. A major difference is that in the MB neurons are not recurrently connected, while in a Reservoir Network they are. SVMs also use projection into high-dimensional spaces, and it is perhaps due to this commonality that cyborgs were less beneficial to SVMs than to NNs and Nearest Neighbors.

**Role of the competitive inhibition layer**  The competitive inhibition layer may enhance classification by creating several attractor basins for inputs, each focused according to which subsets of features present most strongly, which in turn depends on the classes. This might serve to push otherwise similar samples (of different classes) away from each other, towards their respective class attractors, increasing the effective distance between the samples. Thus the outputs of the AL, after this competitive inhibition, may have better separation by class.

However, in our experiments on this particular dataset, while the competitive inhibition layer (AL) did benefit the downstream ML classifier, it was less important than the sparse layer (MB). We see two reasons why this might so. First, the AL has other jobs to do in the insect olfactory network, such as gain control and corraling inputs from the noisy antennae [24, 25]. Perhaps these are the AL's primary tasks, and separating input signals is a secondary task. Second, the MothNet model was transferred to the vMNIST task from a model developed to study odor learning that was calibrated to in vivo moth data [16]. Perhaps the AL has a larger role in the natural, odor-processing setting, and its transfer to the vMNIST task modified the overall balance of the AL-MB system and reduced the importance of the AL relative to the MB. That said, the best results and also most consistent improvements were posted by full cyborgs, i.e. those generating features using the full AL-MB network.

**Role of Hebbian updates**  We suspect that much of the success of BNNs (and MothNet) is due to the Hebbian update mechanism, which appears to be quite distinct from typical ML weight update methods. It has no objective function or output-based loss that is pushed back through the network as in backprop or agent-based reinforcement learning (there is no “agent” in the MothNet system). Hebbian weight updates, either growth or decay, occur on a local “use it or lose it” basis.

We also suspect that much of the success of the cyborgs was due to the stacking of two distinct update methods, e.g. Hebbian and backprop. In our experience, stacking dissimilar ML methods is more productive than stacking similar methods. This may be one reason MothNet cyborgs delivered improvement to ML accuracy even in cases where the baseline ML accuracy already exceeded the MothNet’s top performance, enabling up to 40% reductions in Test set error: Each system brings unique structure-extracting skills to the data. It may also explain why projecting into the high-dimensional MB is not redundant when paired with an SVM, which also projects into a high-dimensional space: The two methods of learning the projections are different.

**Limitations**  A practical limitation of this method, in its current form, is that MothNet trains on and evaluates samples by the time-evolution of systems of coupled differential equations. This is time-consuming (∼4 seconds per sample), and increases non-linearly for more complex datasets with high-dimensional feature spaces, since these would likely require larger networks with more neurons per layer and thus more equations to evolve. In addition, the time-evolution system does not conveniently mesh with other ML platforms such as Tensorflow. Thus, a key future project is to
develop different methods of running MothNet-like architectures, that shortcut computations of time evolutions and mesh with other platforms, yet functionally preserve a Hebbian update mechanism.

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