1 **Human learning follows the dynamics of gradient descent**

2 Daniel N. Barry¹ and Bradley C. Love^{1,2}

3 1. Department of Experimental Psychology, University College London, 26 Bedford Way,
4 London, WC1H0AP, UK

5 2. The Alan Turing Institute, 96 Euston Road, London, NW12DB, UK

6 Corresponding author: daniel.barry@ucl.ac.uk, ORCID ID: [0000-0002-2474-5651](https://orcid.org/0000-0002-2474-5651)

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Abstract

Artificial neural networks (ANNs) have achieved near human-level performance on many tasks and can account for human behavioural and brain measures in a number of domains. Although a principal strength of ANNs is learning representations from experience, only a handful of contributions have evaluated this process to ask whether ANN learning dynamics provide a good model of human learning. We investigated whether humans learn similarly to an ANN, which adjusts its representations through gradient descent. Gradient descent learning is steep at first and initially ignores covariance between features. ANNs can theoretically display a non-monotonic behaviour in which early in learning, multiple weak predictors determine the ANN's decision whereas late in learning a single strong predictor can dominate. This initial behaviour was confirmed in a simple ANN and in half of human participants performing a comparable task. Later in gradient descent learning, the ANN changed to placing a greater weight on the stronger predictor, and humans also shifted their preferences in the same way. Hidden Markov modelling of the behaviour of ANNs and humans predicted similar transitions from weak-feature to strong-feature states. Our results suggest a significant proportion of people learn about categories in a manner analogous to ANNs, possibly by updating their mental representations by a process akin to gradient descent. Our findings demonstrate how ANNs can be used to not only explain the products of human learning but also the process.

Keywords: category learning, neural network, gradient descent

52 **1. Introduction**

53 Artificial neural networks display human-like capabilities on tasks such as object recognition
54 (He, Zhang, Ren, & Sun, 2015; Russakovsky et al., 2015), speech processing (Graves,
55 Mohamed, & Hinton, 2013; Kell, Yamins, Shook, Norman-Haignere, & McDermott, 2018), and
56 game-playing (Badia et al., 2020; Silver et al., 2018). An outstanding question is whether
57 humans update their representations using ANN-like dynamics. Comparisons with human
58 development suggest parallels. Similar to infants, deep ANNs first learn broad conceptual
59 relationships in hierarchically-structured data (Saxe, McClelland, & Ganguli, 2019). Neural
60 networks also become rapidly sensitive to useful inputs, yielding sudden boosts in
61 performance, and this signature of gradient descent can be observed in comparable stage-
62 like progress observed in children (Munakata & McClelland, 2003). Such non-monotonic
63 learning curves also emerge on a feature level in ANNs, predicting the illusory correlations
64 children often believe are present during category learning (Saxe et al., 2019). Further,
65 learning updates in ANNs and humans can be similarly sensitive to order effects, such as
66 those related to overall category variability (Mareschal, Quinn, & French, 2002) with estimates
67 of variability shaped by trial-to-trial error correction (Sakamoto, Jones, & Love, 2008). Neural
68 network dynamics may therefore contribute to cognitive science by generating predictions
69 about human learning.

70 Category learning is a common task for both humans and ANNs, providing a well-
71 controlled test bed in which we can examine the dynamics of learning, absent prior knowledge.
72 Category learning can be multidimensional and probabilistic; a dog breed may be identified
73 based on multiple imperfectly predictive features such as size, shape and colour. One solution
74 is to begin applying a single rule based on one dimension, adding more later if necessary
75 (Nosofsky & Palmeri, 1998). However, additional category dimensions, whether relevant or
76 not, dilutes human's reliance on individual features, suggesting people favour using multiple
77 cues (Edgell et al., 1996). Evidence supporting either behaviour is mixed. Gluck, Shohamy,
78 and Myers (2002) showed individuals initially rely on one cue in the weather prediction task,

79 before using more later. Alternatively, Lagnado, Newell, Kahan, and Shanks (2006) reported
80 most people base their decisions on multiple cues from the beginning. In this study, will make
81 a neural network-based prediction on how humans solve a categorisation task with multiple
82 features.

83 We predict ANNs will rely on multiple cues early in training, even when doing so is sub-
84 optimal. The predominant mechanism underlying neural network learning is stochastic
85 gradient descent (Rumelhart, Hinton, & Williams, 1986). The gradient informs how a model's
86 weights should change to minimise the difference between its predictions and the data.
87 Weights are changed gradually through descending the error surface (Figure 1B) until optimal
88 values are found. Although the weights in a one-layer network will eventually converge to
89 those from a standard linear regression, gradient descent's incremental nature makes it
90 unlikely that the network will take the most direct route. For example, if similar weight changes
91 are initially applied to all predictive features, the combined weights of multiple weakly
92 predictive features may overshadow a single more useful feature. Although this problem may
93 be exacerbated in a complex non-linear multi-layered network, in principle it should also affect
94 a simple one-layer linear network. We investigated this phenomenon by training a small ANN
95 with three input features, two less predictive than the third, and monitored how the network
96 updates its representations. Using the same design, we compared how human participants
97 learned. We hypothesised both ANNs and human participants would initially assign a higher
98 importance to multiple less predictive features, but this preference would shift towards a
99 stronger feature throughout training.

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101 **2. Materials and methods**

102 **2.1 Neural networks**

103 **2.1.1 Zero-initialised neural network and linear regression**

104 The ANN contained three inputs and one output (Figure 1A). We trained the network on three
105 binary predictor variables, two of which were weaker predictors than the third, and one binary

response variable. The network also had a bias term that was akin to the intercept term in linear regression. Linear regression will assign a greater weight to the stronger feature than the combined weights of the two weaker predictors. Indeed, because of the covariance structure of the predictors (Figure 2A), the weaker predictors have negative weights in the linear regression solution. Gradient descent should initially increase all weights similarly, the combined weaker features overshadowing the stronger one (Figure 1B, dotted line). With further learning, the stronger feature's weight should continue to increase, while the weaker features weights should descend below zero as the model detects a negative covariance between weak and strong predictors. The final solution arrived at by the network (grey ball) should match the weights from linear regression, however gradient descent should take a significant detour along the way.

The ANN weights and bias values were initially set to zero. The network was trained for 4000 blocks to reach convergence; the optimal solution with minimal error. The training objective was to minimise the mean squared error loss. The optimizer used gradient descent with a learning rate of 0.01 and a batch size of 14. The final weights of this network were compared with regression coefficients computed using standard linear regression.

Figure 1. Neural network structure and hypothesised gradient descent trajectory. (A) A simple ANN was trained to predict one outcome variable from three input features, one more strongly predictive than the other two. (B) The hypothesised trajectory of gradient descent along the error surface of the model.

2.1.2 Randomly initialised neural networks

To compare neural network behaviour more closely with a sample of human participants, we additionally trained 102 randomly initialised networks (to match the number of human participants, see section 2.2.1), and added noise (mean: 0, SD: 0.1) to the learned weights.

2.1.3 Analysis

2.1.3.1 Proportion of neural networks using different features for categorisation

We calculated the proportion of the randomly initialised networks relying more on the combined weaker weights, or a single stronger weight for each of the 4000 blocks.

2.1.3.2 Hidden Markov modelling

To investigate how the randomly initialised networks updated their representations, we obtained the network's decisions based on the feature weights and fitted a Hidden Markov Model (HMM). Here, the objective is to determine the state which is producing a behaviour. However, the state is not directly observable and must be inferred from a sequence. Using the Expectation-Maximisation algorithm, we searched for the maximum likelihood of a number of parameter estimates. These were the probability of transitioning from one state to another from time t to $t+1$, generating a state transition matrix, and the probability of emitting a symbol in that state, known as emission probabilities. As the data involved a binary decision, we used a multinomial HMM using the hmmlearn toolbox (<https://github.com/hmmlearn/hmmlearn>). We constrained the ANN and human analysis to have the same number of states (see section 2.3). To facilitate interpretation, we assigned labels to each of the states based on the emissions probabilities.

2.2 Human category learning task

2.2.1 Participants

One hundred seventy-four participants were recruited via the online crowdsourcing platform MTurk (www.mturk.com). Informed consent was obtained prior to experimentation. The task was hosted on the online platform Gorilla (<https://app.gorilla.sc/>). Seventy-two participants failed to learn the task and were excluded (see section 2.3.2). The average age of the remaining 102 participants was 36 (SD 10). Fifty-two participants identified as female and 48 as male.

2.2.2 Training

The three binary predictor variables were features of bugs, namely antennae, mouth, and legs (Figure 2B). Each bug belonged to one of two categories. Category labels were generated by the pseudoword generator “Wuggy” (Keuleers & Brysbaert, 2010). The associations between bug features and labels matched those used during ANN training (Figure 2A). Participants viewed 14 bugs consecutively; each appeared on screen followed by its label (Figure 2C). The assignment of bug features to being the stronger or one of the weaker predictors was counterbalanced across participants, as were six different sets of labels.

Participants underwent 10 training blocks with the same 14 images presented in a random order. After each block, we tested whether participants had learned the basic associations between features and their probabilistic outcomes. In these two “prototype” trials, all three features were predictive of the same category label, and if participants were not responding correctly on these final four trials, they were excluded from the analysis. Of primary interest was the remaining participant’s performance on two “conflict” trials, where one feature strongly predicted one category, while the other two weakly predicted another (Figure 2D). In the four test trials participants were asked to rate on a sliding scale how likely the bug was to belong to either category.

Figure 2. The human category learning task. (A) During training, participants were shown 14 bug images, one at a time, which contained a combination of three features. Two of the three features were less predictive of the bug's category (shaded blue-10/14 trials) than the third (shaded red-12/14 trials). During testing, participants were asked to identify the category of prototype bugs, where each feature was predictive of a single category, and conflict bugs, where features predicted different categories. (B) The three bug features which could each differ in two ways: a thick or thin antennae, a pincer or shovel mouth, and thick or thin legs. (C) Participants viewed each bug image followed by its label. (D) A sample conflict trial, where one feature (mouth) strongly predicted the category "Angen", whereas the two other features (antennae and legs) were weaker predictors of the category "Wicher".

2.2.3 Analysis

2.2.3.1 Proportion of participants using different features for categorisation

To investigate whether people relied on a single “stronger” feature to classify an object, or multiple “weaker” features, and how this changed across learning, we recoded participant’s rated probabilities of category membership on each conflict trial into a binary decision, and calculated the proportion of participants using the different features.

2.2.3.2 Hidden Markov modelling

To further investigate how participants updated their learning representations, we modelled their category decisions using a Hidden Markov Model (HMM). To determine the number of states which explained our data we calculated the Bayesian Information Criterion (BIC) for models containing two to eight states. BIC is based on the likelihood of each model, but penalises complex models containing more free parameters. The model with the lowest BIC value was one with three states (see supplementary material). We fitted a three-state HMM to the 20 conflict trials across 102 participants.

3. Results

3.1 Evolution of feature weights during gradient descent learning

Our simulation investigated how gradient descent assigns weights to different features over the course of learning in an ANN. Each item had three binary predictors (plus a bias term) and a binary outcome variable. The linear regression solution was a weight of 1.0 for the stronger feature and -.2 for each weaker feature (Figure 3A). While gradient descent converged to the same solution, it followed a path in which the weaker features dominated early in learning with the optimal strong feature emphasised later in learning. This simulation suggests that gradient descent may be biased towards abundant but poorly predictive features early in training, before the optimal solution is found. A sample of 102 randomly initialised neural networks performing the same task, which attempted to predict the behaviour of a group of humans, revealed that approximately half of networks began using the weaker cues, slowly transitioning to using the stronger one on a group level (Figure 3B). A three-state HMM found that nearly

half of the sample of neural networks begin training highly confident about the importance of the weaker weights (Figure 3C). The model predicted a gradual sequential transition to two “strong feature” states, the first unsure, and the final state highly confident.

Figure 3. Dynamic changes in feature weights during gradient descent in neural networks. (A) The weights assigned by a zero-initialised ANN to two weakly predictive features or one strongly predictive feature throughout training, compared with the weights of a linear regression. (B) The proportion of a sample of 102 randomly initialised neural networks placing greater weights on combined weaker features or a single stronger one throughout training. (C) A three-state hidden Markov model of the randomly initialised neural network behaviour. (EP = emission probability, transition probabilities between and within states displayed adjacent to arrows. Transition probabilities less than 0.0001 are not displayed)

3.2 Human reliance on category features throughout learning

We then investigated whether people update their representations like ANNs when faced with a comparable learning problem. Figure 4A shows the proportion of participants who assigned a greater importance to the stronger feature, or the two weaker features, across the 20 conflict trials. Participants were equally likely to rely on the strong or weak features at the beginning of training, however an increasing proportion of participants chose the category associated with the stronger feature as training progressed. This gradual shift on a group level closely resembled the behaviour of a sample of randomly initialised ANNs.

We fit a HMM to participant's sequences of decisions. Three hidden states emerged from this analysis (Figure 4B). Similar to the sample of ANNs, a significant proportion (36%) of people were highly confident that the two weaker features were more predictive at the beginning of training. Also reflective of the shift from two-weak to one-strong predictor in ANNs, these participants were likely to transition to a state where they chose the strong feature most of the time. As with the ANN HMM, the human HMM predicted an ultimate transition to a state where they were highly confident about the predictive ability of the strong feature, and would remain in that state.

Figure 4. Individual differences in behaviour throughout human category learning. (A) The proportion of human participants throughout training who chose to classify stimuli based on either one strongly predictive cue or two cues which were more weak predictors.

(B) A HMM fit to participant's responses revealed three states influencing their decisions. (EP = emission probability, transition probabilities between and within states displayed adjacent to arrows. Transition probabilities less than 0.0001 are not displayed)

4. Discussion

We found that the category learning behaviour of human participants could be predicted by the gradient descent updates of randomly initialised simple ANNs performing a similar task. In both cases there was a sub-optimal tendency to begin by relying on multiple weakly predictive cues. Further, humans and ANNs were inclined to change their mind during training and shift their attention towards a stronger feature. This suggests people may share learning mechanisms which mirror those of gradient descent, assigning similar weighting to all predictive features initially and treating them as cumulatively diagnostic of a category. Our results offer a potential mechanistic explanation for previous work in humans demonstrating that the presence of multiple, even redundant cues, can dilute the reliance on stronger ones (Edgell et al., 1996). In the same vein, our results posit a mechanism through which humans and ANNs are vulnerable to being misled by shortcuts, features which are more abundant or obvious at first, but which are not the best predictors of a category (Dagaev et al., 2021). We note that the magnitude of the weight differences in an ANN can be modest at the beginning of training, but we show in a group of neural networks that this would be sufficient to affect behaviour, and reflect that observed in a human sample. While some reservations remain about whether the brain performs computations exactly like gradient descent via backpropagation (Lillicrap, Santoro, Marris, Akerman, & Hinton, 2020), ANNs which learn this way predict visual brain responses to objects better than any other biologically-inspired models (Cadieu et al., 2014).

We observed in both humans and a group of randomly-initialised ANNs that the shift from a focus on multiple cues to a single cue was gradual, with many people were still relying on the weak cues at the end of training, and many neural networks were still using them after

1000 blocks. This slow learning may be interpreted as “blocking”; the resistance to learning about a new cue when another has been learned previously (Rescorla & Wagner, 1972). This has previously been regarded as a product of error-driven learning. However, our results may reveal another significant influence on this phenomenon, that there may be a human analogue of random weight initialisation, whereby pre-existing random biases towards a feature may slow down the updating of category representations.

Prior work using the weather prediction task has been equivocal regarding whether the majority of participants use multiple cues (Lagnado et al., 2006) or a single cue (Gluck et al., 2002) early in category learning. Our task differed from the classic weather prediction task, in that relying on a single strong cue was most efficient, providing a more stringent test of whether people naturally tend towards incorporating multiple cues into their representations. Despite the latter behaviour being sub-optimal, 49% of participants began training in this manner, 36% acting with high confidence. These results reveal substantial individual differences across individuals, with some people naturally inclined to adopt a RULEX approach, using a single dimension to classify an object and only adding more if necessary (Nosofsky & Palmeri, 1998), and others tending to combine across multiple features. Our study has advantages over prior work, benefitting from a larger sample size ($n=102$), than the Gluck et al. (2002) ($n=30$) and Lagnado et al. (2006) ($n=12-16$) studies, yielding more generalisable results. Further, the integrated realistic stimuli we used reflect the naturalistic way humans learn about multidimensional categories (Mack, Love, & Preston, 2016), in contrast to the separate abstract patterns used in the weather prediction task.

We acknowledge that this study did not evaluate complex tasks, or use a model which builds complex category representations, such as a clustering model (Love & Medin, 1998). However, this work represents an initial exploration into how people and ANNs can share similar learning dynamics. We hope our results complement prior work, which has revealed similar learning behaviours (Mareschal et al., 2002; Munakata & McClelland, 2003; Saxe et al., 2019) and neural representations (Güçlü & van Gerven, 2015; Khaligh-Razavi & Kriegeskorte, 2014) across humans and ANNs. Neural networks therefore serve to provide

both a mechanistic account and generate specific, and perhaps unexpected, predictions about human behaviour, which might not be compatible with a rational account (Sakamoto et al., 2008), and might not apply to everyone. The human-like behaviour we observed in our simple ANNs may also be consequential for the design of autonomous artificially intelligent agents who engage in continual learning, as they may make sub-optimal decisions early in learning due to the tendency to assign a greater combined importance to less predictive cues. Therefore, although the accuracy of fully trained ANNs can be impressively high (Schrimpf et al., 2018), they may make mistakes similar to those made by humans as they learn about the world.

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Data and code availability: The code and environment required to train the ANN and run the HMM are available at:

https://github.com/danielbarry1/human_learning_gradient_descent

All data in the paper, as well as experimental stimuli and instructions, are available at

<https://doi.org/10.6084/m9.figshare.16930717>.

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