FORTUITOUS FORGETTING IN CONNECTIONIST NETWORKS

Anonymous authors
Paper under double-blind review

ABSTRACT

Forgetting is often seen as an unwanted characteristic in both human and machine learning. However, we propose that forgetting can in fact be favorable to learning. We introduce *forget-and-relearn* as a powerful paradigm for shaping the learning trajectories of artificial neural networks. In this process, the forgetting step selectively removes undesirable information from the model, and the relearning step reinforces features that are consistently useful under different conditions. The forget-and-relearn framework unifies many existing iterative training algorithms in the image classification and language emergence literature, and allows us to understand the success of these algorithms in terms of the disproportionate forgetting of undesirable information. We leverage this understanding to propose more targeted forgetting steps, and show that they significantly improve upon existing algorithms. We reduce overfitting in image classification by repeatedly forgetting later layers of the network. We promote compositionality in the communication between agents in a referential game through partial weight perturbations. Insights from our analysis provide a coherent view on the dynamics of iterative training in neural networks and offer a clear path towards performance improvements.

1 INTRODUCTION

Forgetting is an inescapable component of human memory. It occurs naturally as neural synapses get removed or altered over time (Wang et al., 2020), and is often thought to be an undesirable characteristic of the human mind. Similarly, in machine learning, the phenomena of catastrophic forgetting is often blamed for certain failure modes in the performance of neural networks (McCloskey & Cohen, 1989; Ratcliff, 1990; French, 1999)[1]. However, substantial evidence in psychology and neuroscience have shown that forgetting and learning have a symbiotic relationship (Bjork & Bjork, 2019; Gravitz, 2019). A well-known example is the "spacing effect", which refers to the observation that long-term recall is enhanced by spacing, rather than massing, repeated study sessions. Bjork & Allen (1970) demonstrated that the key to the spacing effect is the decreased accessibility of information in-between sessions.

In this work, we study a general learning paradigm that we refer to as *forget-and-relearn*, and show that forgetting can also benefit learning in artificial neural networks. To generalize to unseen data, we want our models to capture generalizable concepts rather than purely statistical regularities, but these desirable solutions are a small subset of the solution space and often more difficult to learn naturally (Geirhos et al., 2020). Recently, a number of training algorithms have been proposed to improve generalization by iteratively refining the learned solution. Knowledge evolution (Taha et al., 2021) improves generalization by iteratively reinitializing one part of the network while continuously training the other. Iterative magnitude pruning (Frankle & Carbin, 2018; Frankle et al., 2019) removes weights through an iterative pruning-retraining process, and outperforms unpruned models in certain settings. Hoang et al. (2018) iteratively utilize synthetic machine translation corpus through back-translations of monolingual data. Furlanello et al. (2018); Xie et al. (2019) employ iterative self-distillation to outperform successive teachers. Iterated learning[2] (Kirby, 2001) has been shown to improve compositionality in emergent languages (Ren et al., 2020; Vani et al., 2021) and

[1]Our paper title is derived from that of French (1999), *Catastrophic Forgetting in Connectionist Networks*.

[2]We distinguish the use of the term "iterated learning" (IL), which is a specific algorithm, with "iterative training", which refers to any training procedure that includes multiple generations of training.

prevent language drift (Lu et al., 2020). We propose that many existing iterative algorithms are instances of a more general forget-and-relearn process, and that their success can be understood by studying the shared underlying mechanism.

Forget-and-relearn is an iterative training paradigm which alternates between a forgetting stage and a relearning stage. At a high level, we define a forgetting stage as any process that results in a decrease in training accuracy. More specifically, let $\mathcal{D} = \{(X_i, Y_i)\}_{i \in [n]}$ be the training dataset. Let U represent uniform noise sampled from $(0, 1)$, which we use as a source of randomness for stochastic functions. Given a neural architecture, let $\mathcal{F}$ be the set of functions computable by a neural network with that architecture, and for any $N \in \mathcal{F}$, let $\text{Acc}(N) = \frac{1}{n} \sum_{i=1}^{n} \mathbb{I}\{N(X_i) = Y_i\}$ be the training accuracy of N. Let N_t be a network trained on $\mathcal{D}$, and let $C := E[\text{Acc}(\tilde{N})]$ represent the performance of a randomly initialized classifier on $\mathcal{D}$. We say that $f : \mathcal{F} \times (0, 1) \to \mathcal{F}$ is a *forgetting operation* if two conditions hold: (i) $P(\text{Acc}(f(N_t, U)) < \text{Acc}(N_t) \mid \text{Acc}(N_t) > C) = 1$; (ii) the mutual information $I(f(N_t, U), \mathcal{D})$ is positive. The first criterion ensures that forgetting will allow for relearning due to a decrease in accuracy. The second criterion captures the idea that forgetting equates to a partial removal of information rather than a complete removal. For standard neural networks, it is sufficient to show that training accuracy is lower than the model prior to forgetting, but higher than chance accuracy for the given task.

The Forget-and-Relearn Hypothesis. *Given an appropriate forgetting operation, iterative retraining after forgetting will amplify unforgotten features that are consistently useful under different learning conditions induced by the forgetting step. A forgetting operation that favors the preservation of desirable features can thus be used to steer the model towards those desirable characteristics.*

We show that many existing algorithms which have successfully demonstrated improved generalization have a forgetting step that disproportionately affects undesirable information for the given task. Our hypothesis stresses the importance of selective forgetting, and shows a path towards better algorithms. We illustrate the power of this perspective by showing that we can significantly improve upon existing work in their respective settings through the use of more targeted forgetting operations. Our analysis in Section 5 sheds insight on the mechanism through which iterative retraining leads to parameter values with better generalization properties.

2 Existing Algorithms as Instances of Forget-and-Relearn

In this section and the rest of the paper, we focus on two settings where iterative training algorithms have been proposed to improve performance: image classification and language emergence. We summarize a number of these iterative training algorithms, and recast them as instances of the forget-and-relearn process by highlighting the forgetting operation in these methods. We also provide a discussion relating our notion of forgetting to other ones in the literature in Appendix A5.

Image Classification. A number of iterative algorithms for image classification uses a reinitialization and retraining scheme, and these reinitialization steps can be seen as a simple form of forgetting. Iterative magnitude pruning (IMP) (Frankle & Carbin, 2018; Frankle et al., 2019) removes weights based on final weight magnitude, and does so iteratively by removing an additional percentage of weights each round. Each round, small magnitude weights are set to zero and frozen, while the remaining weights are rewound to their initial values. Zhou et al. (2019a) show that the masking and weight rewinding[3] procedure still retains information from the previous training round by demonstrating that the new initialization achieves better-than-chance accuracy prior to retraining. Thus, we can view IMP as a forget-and-relearn process with an additional sparsity constraint. RIFLE (Li et al., 2020) shows that transfer learning performance can be improved by periodically reinitializing the final layer during the finetuning stage, which brings meaningful updates to the low-level features in earlier layers. We can view this reinitialization step as a forgetting operation that enables relearning.

Knowledge evolution (KE) (Taha et al., 2021) splits the network's weights into a *fit-hypothesis* and a *reset-hypothesis*, and trains the network in generations in order to improve generalization performance. At the start of each generation of training, weights in the reset-hypothesis are reinitialized,

[3]In this work, we use "rewind" to mean resetting weights back to their original initialization. We use "reset" and "reinitialize" interchangeably to indicate a new initialization.

while weights in the fit-hypothesis are retained. Taha et al. (2021) suggest that KE is similar to dropout where neurons learn to be more independent. However, it is hard to translate the dropout intuition to the case of a single subnetwork. Another intuition compares to ResNet, since KE can induce a zero mapping of the reset-hypothesis without reducing capacity. But this zero-mapping always occurs with sufficient training, and it is unclear why it would benefit generalization.

Language Emergence. Several existing algorithms in the language emergence subfield can also be seen as forget-and-relearn algorithms. Emergent communication is often studied in the context of a multi-agent referential game called the Lewis game (Lewis, 2008; Foerster et al., 2016; Lazaridou et al., 2016). In this game, a sender agent must communicate information about the attributes of a target object to a receiver agent, who then has to correctly identify the target object. Compositionality is a desirable characteristic for the language that agents use, as it would allow for perfect out-of-distribution generalization to unseen combinations of attributes.

Li & Bowling (2019) hypothesize that compositional languages are easier to teach, and propose an algorithm to exert an "ease-of-teaching" pressure on the sender through periodic resetting of the receiver. We can instead view the receiver resetting as partial forgetting in the multi-agent model. Ren et al. (2020) use iterated learning (IL) to improve the compositionality of the emergent language. Their algorithm consists of (i) an interacting phase where agents learn to solve the task jointly, (ii) a transmitting phase where a temporary dataset is generated from the utterances of a sender agent, and (iii) an imitation phase where a newly-initialized sender is pretrained on a temporary dataset of the previous sender's utterances, before starting a new interacting phase, and this process iterates. A crucial component during imitation is to limit the number of training iterations, which creates a learning bottleneck that prevents the new model from fully copying the old model. This restricted transfer of information can be seen as a forgetting operation, and showcases an alternative approach to selective forgetting that removes information that is harder to learn.

3 Partial Weight Perturbation as Targeted Forgetting

In this section, we show that common forms of partial weight perturbation disproportionately affect information that can hinder generalization in both image classification and language emergence settings, and can thus be seen as a targeted forgetting operation under the forget-and-relearn hypothesis. We provide full details on the perturbation method studied in Appendix A1.1.

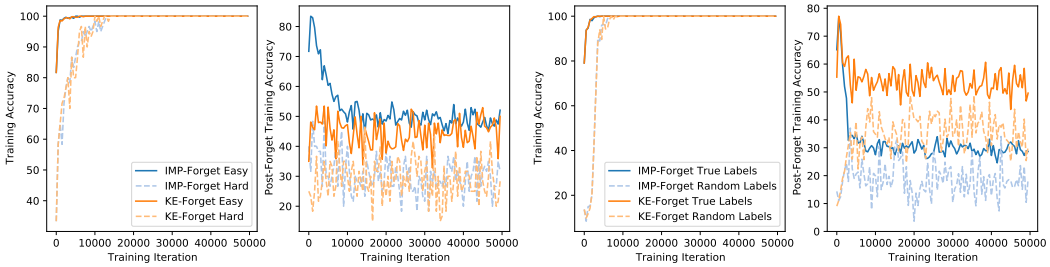
3.1 Image Classification

What information is undesirable depends on the task at hand. For the issue of overfitting in image classification, we want to favor features that are simple, general and beneficial for generalization (Valle-Pérez et al., 2019). Several works have shown that easy examples are associated with locally simpler functions and more generalizable features, while difficult examples require more capacity to fit and are often memorized (Baldock et al., 2021; Yosinski et al., 2014; Nakkiran et al., 2019; Arpit et al., 2017). Thus, as a proxy, we define *undesirable information* here as features associated with memorized examples. In order to evaluate whether partial weight perturbation selectively forgets undesirable information, we create two types of example splits for our training data: (i) easy or difficult examples, and (ii) true or mislabeled examples. At each training iteration, we make a copy of the model and perform a forgetting operation on the copy. We then evaluate both models and measure separately the training accuracy on the two groups of examples. We perform these experiments using a two-layer MLP trained on MNIST. We further extend to a 4-layer convolution model and a ResNet18 on CIFAR-10, and to ResNet50 on ImageNet in Section A1.2. [4]

For the definition of easy or difficult examples, we follow prior work (Jiang et al., 2019; Baldock et al., 2021) and use the output margin as a measure of example difficulty. The output margin is defined as the difference between the largest and second-largest logits. We label 10% of training examples with the smallest output margin in the current batch as difficult examples. In the noisy labels experiment, we sample 10% of the training data[5] and assign random labels to this group.

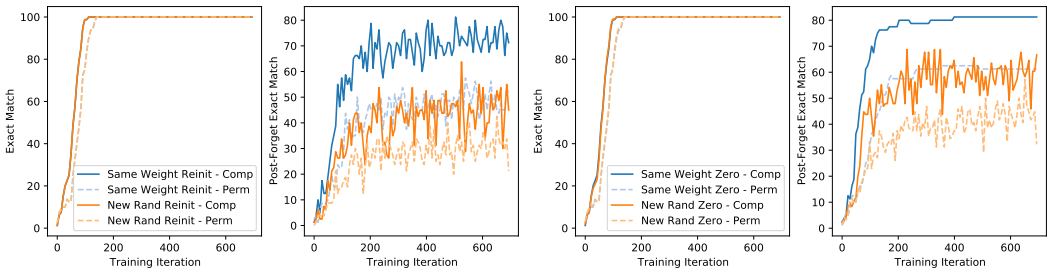
[4] We use an MLP with hidden layers 300-100-10, trained using SGD with a constant learning rate of 0.1.

[5] To simplify the task, we restrict to using only 10% of the MNIST training set so that the random label examples can be learned quickly.



(a) Easy vs difficult examples. (b) True vs mislabeled examples.

Figure 1: The left panels in (a) and (b) show training accuracy of the two example groups for two types of weight perturbation. The right panels in (a) and (b) show the accuracy of each example group for the same model with weight perturbation applied. Same colors represent the same forgetting operation, and dashed lines represent the accuracy on the difficult or mislabeled examples. Results are averaged over 5 runs.



(a) Perturb through reinitialization of masked weights. (b) Perturb through setting masked weights to 0.

Figure 2: The left panels in (a) and (b) show train accuracy of the compositional (Comp) and non-compositional (Perm) language examples; blue lines here are hidden behind orange lines. The right panels in (a) and (b) show the accuracy of each group for the same model with weight perturbation applied. Same colors represent the same forgetting operation, and dashed lines represent the accuracy on the non-compositional examples. Results are averaged over 5 runs.

We consider KE-style perturbation to be the reinitialization of a random subset of the weights, and IMP-style perturbation to be the zeroing of small magnitude weights and rewinding of the remaining weights. More details are provided in Table A1. Figure 1 shows that both types of weight perturbation adversely impact difficult or mislabeled example groups more severely than the easy or true labeled examples, even when both example groups reach 100% train accuracy. Related to our observations, Hooker et al. (2021) show that pruned models disproportionately affect tails of the data distribution. There are also theoretical works tying robustness-to-parameter-noise to compressibility, flat minima, and generalization (Zhou et al., 2019b; Arora et al., 2018; Foret et al., 2021).

3.2 Compositional Language Emergence

In the version of the Lewis game we study, the objective is to identify objects with two attributes: SHAPE and COLOR. The sender receives a one-hot representation of the SHAPE and COLOR attributes of an object and produces a discrete message. The receiver takes this message as input and needs to classify the correct object from a set of candidate objects. The two agents are typically parameterized as LSTMs (Hochreiter & Schmidhuber, 1997) and trained simultaneously using REINFORCE (Williams, 1992) or Gumbel-softmax (Jang et al., 2017; Maddison et al., 2017). A compositional language would have a consistent and independent attribute-symbol mapping for all input objects. This is desirable for out-of-distribution generalization, since unseen combinations of attributes will still have a meaningful language output. Thus, the *undesirable information* in this task corresponds to a non-compositional language. We define two candidate languages as designed by Li & Bowling

(2019), that are used to provide possible targets to the model. One language is compositional, where each attribute (8 shapes and 4 colors) is represented by a distinct and consistent symbol-position. The other language is non-compositional, which is formed by randomly permuting the mappings between messages and objects from the compositional language. In this case, each object still has a unique message, but the individual symbols do not correspond to a consistent meaning for shape or color. An example of a compositional and permuted language is provided in Table A2 and A3.

Since the sender controls the language output, here we simplify the Lewis game and train only the sender model to fit a given language through supervised learning. The target language is formed by mixing the two target languages. For the 32 objects in the training set, half of them are mapped to the compositional language and half to the non-compositional language. Similar to the experiments in Section 3.1, we make a copy of the model at each training iteration, and perform the forgetting operation on the copy. We evaluate both models and measure the accuracy of the two example groups separately. For the weight perturbations, we consider either a mask based on initial weight magnitude or a random mask. For both mask criteria, we either reinitialize the masked weights or set them to 0. More details can be found in Table A4. As shown in Figure 2, we find that all forms of weight perturbation under study lead to more forgetting of the non-compositional language.

4 Targeted Forgetting Improves Performance

According to the forget-and-relearn hypothesis, the forgetting step should strike a balance between enabling relearning in the next generation and retaining desirable information from the previous generation. We show in this section that through targeted forgetting of undesirable information and preserving of desirable information, we can significantly improve upon existing algorithms.

4.1 Reducing Overfitting in Image Classification

We build upon the KE algorithm since it is widely applicable and leverages a large number of iterative training generations. Following Taha et al. (2021), we study tasks that have a small number of training examples per class, where the network is prone to overfitting. and adopt the same experimental framework unless otherwise specified. Detailed hyperparameters, training procedure, and dataset descriptions can be found in Appendix A2.1-A2.2.

As described by Taha et al. (2021), in KE the mask criteria M is determined prior to training and generated randomly for weight-level splitting (WELS), or based on the location of the kernel for kernel-level splitting (KELS). Given a split-rate s_r, $s_r\%$ of weights (for WELS) or kernels (for KELS) in each layer l has a corresponding M^l value of 1. For a neural network parameterized by $\mathbf{\Theta}$, we define the *fit-hypothesis* as $M \odot \mathbf{\Theta}$ and *reset-hypothesis* as $(1 - M) \odot \mathbf{\Theta}$. At the start of each generation, the weights in the fit-hypothesis are kept the same, and the weights in the reset-hypothesis are reinitialized. Then, the network is trained from this new initialization for e epochs, where e is the same for each generation.

Can we perform the forgetting step in a way that more explicitly targets difficult examples in order to improve generalization performance? Baldock et al. (2021) introduce *prediction depth* as a measure of example difficulty in a given model. Prediction depth refers to the layer after which an example's activations can generate the same predictions using a KNN probe as the model's final predictions. They show that increasing prediction depth corresponds to increasing example difficulty. They study this correspondence using various notions of example difficulty, including output margin, adversarial input margin, and speed of learning for each data point.

Based on the observations in Baldock et al. (2021), we hypothesize that by reinitializing the later layers of the neural network, we can remove information associated with difficult examples more precisely than the mask criteria used in KE. Thus, we propose a new forgetting procedure called *later-layer forgetting (LLF)*. Given a layer threshold L, we define the LLF mask criterion for each layer l as:

$$M^l_{\text{LLF}} = \begin{cases} 1 & \text{if } l < L \\ 0 & \text{if } l \geq L \end{cases} \tag{1}$$

Note that we use difficult examples only as a proxy for information in the network that is more complex, brittle, and specialized; we do not suggest that these examples should not be learned. In fact,

memorization of examples in the tails of the data distribution are often important for generalization (Feldman & Zhang, 2020), which we also achieve in the relearning stage.

Following Taha et al. (2021), we perform LLF on top of non-iterative loss objectives designed to reduce overfitting. We report performance with label-smoothing (SMTH) (Müller et al., 2019; Szegedy et al., 2015) with $\alpha = 0.1$, and the CS-KD regularizer (Yun et al., 2020) with $T = 4$ and $\lambda_{\text{cls}} = 3$. Additionally, we add a long baseline which trains the non-iterative method for the same total number of epochs as the corresponding iterative methods. We present results for ResNet18 (He et al., 2015) in Table 1 and DenseNet169 (Huang et al., 2018) in Table A9. We find that LLF substantially outperforms both the long baseline and the KE models across all datasets for both model architectures.

Taha et al. (2021) introduced KE to specifically work in the low data regime. LLF as a direct extension of KE is expected to work in the same regime. In Section A2.3, we evaluate LLF using ResNet50 on Tiny-ImageNet, which represents a large scale dataset while still having only 500 images per class. We also evaluate on standard datasets like CIFAR-10 and CIFAR-100 on competitive baselines. We observe a significant gain for Tiny-ImageNet, and no significant difference on CIFAR.

Analysis of Related Work. Surprisingly, we find that when compared to the long baselines with equal computation cost, KE actually *underperforms* in terms of generalization performance, which is contrary to the claims in Taha et al. (2021). We can understand this low performance by looking at the first few training epochs in each generation in Figure 3a. We see that after the first generation, the training accuracy remains near 100% after the forgetting operation. This lack of forgetting suggests that KE would not benefit from retraining under the forget-and-relearn hypothesis. We also observe that KE experiences optimization difficulties post forgetting, as evidenced by a decrease in training accuracy in the first epochs of each generation. This could explain why it under-performs the long baseline. Although KE can enable a reduction in inference cost by using only the slim fit-hypothesis, our analysis reveals that this benefit comes at the cost of lower performance.

Concurrent work (Alabdulmohsin et al., 2021) studies various types of iterative reinitialization approaches and propose a layer-wise reinitialization scheme, which proceeds from bottom to top and reinitializing one fewer layer each generation. We refer to this method as LW and provide a comparison to their method in Table 1. We find that LLF outperforms LW across all datasets we consider. More discussion on this comparison can be found in Appendix A2.4.

Analysis of LLF. In order to view the success of LLF and other similar iterative algorithms in terms of the selective forgetting of undesirable information, we should also observe that selective forgetting of *desirable* information should lead to worse results. We can test this by reversing the LLF procedure: instead of reinitializing the later layers, we can reinitialize the earlier layers. The standard LLF for Flower reinitializes all layers starting from block 4 in ResNet18, which amounts to reinitializing 75% of parameters. The reverse versions starting from block 4 and block 3 reinitializes 25% and 6% of weights respectively. We see in Figure 3b that the reverse experiments indeed perform worse than both LLF and the long baseline.

Additionally, by looking at how prediction depth changes with the long baseline compared to LLF training in Figure A2, we can observe that LLF pushes more examples to be classified in the earlier layers. This further suggests that forget-and-relearn with LLF encourages difficult examples to be relearned using simpler and more general features in the early layers.

4.2 Increasing Compositionality in Emergent Languages

In order to promote compositionality in the emergent language, Li & Bowling (2019) propose to periodically reinitialize the receiver during training. They motivate this by showing that it is faster for a new receiver to learn a compositional language, and hypothesize that forcing the sender to teach the language to new receivers will encourage the language to be more compositional. As is common in this line of work (Brighton & Kirby, 2006; Lazaridou et al., 2018; Li & Bowling, 2019; Ren et al., 2020), compositionality of the language is measured using topographic similarity (ρ), which is defined as the correlation between distances of pairs of objects in the attribute space and the corresponding messages in the message space. Li & Bowling (2019) show that ρ, measured using Hamming distances for objects and messages, is higher with the ease-of-teaching approach than training without resetting the receiver.

Table 1: Comparing KE and Later Layer Forgetting for ResNet18. Results are averaged over 3 runs and reported for hyperparameter settings with best validation performance. KE experiments use KELS split with a split rate of 0.8. LLF uses $L \in \{10, 14\}$, corresponding to block 3 and 4 in ResNet18. N3, N8, N10 indicate the additional number of training generations on top of the baseline model. LLF consistently outperforms all other methods.

Method	Flower	CUB	Aircraft	MIT	Dog
Smth (N1)	51.02	58.92	57.16	56.04	63.64
Smth long (N3)	59.51	66.03	62.55	59.53	65.39
Smth + KE (N3)	57.95	63.49	60.56	58.78	64.23
Smth + LLF (N3) **(Ours)**	**63.52**	**70.76**	**68.88**	**63.28**	**67.54**
Smth long (N10)	66.89	70.50	65.29	61.29	66.19
Smth + KE (N10)	63.25	66.51	63.32	59.58	63.86
Smth + LLF (N10) **(Ours)**	**70.87**	**72.47**	**70.82**	**64.40**	**68.51**
Smth + LW(-BN) NoNorm NoRescale (N8)	68.43	70.87	69.10	61.67	66.97
Smth + LLF (N8) **(Ours)**	**69.48**	**72.30**	**70.37**	**63.58**	**68.45**
CS-KD (N1)	57.57	66.61	65.18	58.61	66.48
CS-KD long (N3)	64.44	69.50	65.23	57.16	66.43
CS-KD + KE (N3)	63.48	68.76	67.16	58.88	67.05
CS-KD + LLF (N3) **(Ours)**	**67.20**	**72.58**	**71.65**	**62.41**	**68.77**
CS-KD long (N10)	68.68	69.59	64.58	56.12	64.96
CS-KD + KE (N10)	67.29	69.54	68.70	57.61	67.11
CS-KD + LLF (N10) **(Ours)**	**74.68**	**73.51**	**72.01**	**62.89**	**69.20**
CS-KD + LW(-BN) NoNorm NoRescale (N8)	**73.72**	71.81	70.82	59.18	68.09
CS-KD + LLF (N8) **(Ours)**	73.48	**73.47**	**71.95**	**62.26**	**69.24**

We challenge this "ease-of-teaching" interpretation in Li & Bowling (2019) and offer an alternative explanation. Instead of viewing the resetting of the receiver as inducing an ease-of-teaching pressure on the sender, we can view it as an asymmetric form of forgetting in the two-agent system. This form of forgetting is sub-optimal, since we care about the quality of the *messages*, which is controlled by the sender. This motivates a balanced forgetting approach for the Lewis game, whereby both sender and receiver can forget non-compositional aspects of their shared language. Therefore, we propose an explicit forgetting mechanism that removes the asymmetry from the Li & Bowling (2019) setup. We do this by partially reinitializing the weights of both the sender and the receiver and refer to this method as *partial balanced forgetting (PBF)*. We use the "same weight reinit" perturbation method from Section 3.2 with 90% of weights masked. Further training details are found in Appendix A3. We show in Figure 4c that this method, which does not exert an "ease-of-teaching" pressure, significantly outperforms both no resetting and resetting only the receiver in terms of ρ.

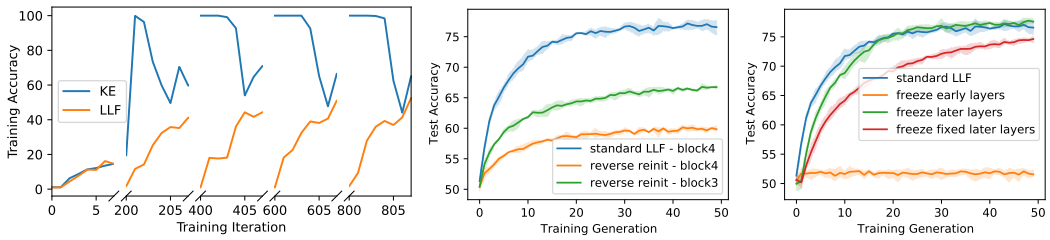
5 Understanding the Forget-and-Relearn dynamic

In Section 4, we discussed the importance of targeted forgetting in the forget-and-relearn dynamic. In this section, we study the mechanism through which iterative retraining shapes learning.

5.1 Image Classification

We consider two hypotheses for why iterative retraining with LLF helps generalization. We note that these hypotheses are not contradictory and may both be true.

1. *Later layers* improve during iterative retraining with LLF. Due to co-adaptation during training, the later layers may be learning before the more stable early layer features are fully developed (notably in early epochs of the first generation), which might lead to more overfitting in the later



(a) Train accuracy at initialization and in the first 6 epochs of training for 5 generations.

(b) Test accuracy of resetting early layers vs. later layers

(c) Test accuracy for different freeze layer settings

Figure 3: Analysis experiments performed on Flower dataset with ResNet18. (b)-(c) show the min, max, and average of 3 runs. (a) shows that KE induces no forgetting after the first 2 generations. (b) shows that resetting early layers significantly under-performs LLF. (c) shows that freezing early layers prevents any improvement in subsequent training, while freezing later layers still leads to significant improvements.

layers. Reinitializing the later layers might give them an opportunity to be relearned by leveraging fully developed features from the earlier layers.

2. *Early layers* improve during iterative retraining with LLF. Since the early layers are continuously refined through iterative training, the features which are consistently useful under new learning conditions may be amplified. These features may be beneficial to generalization.

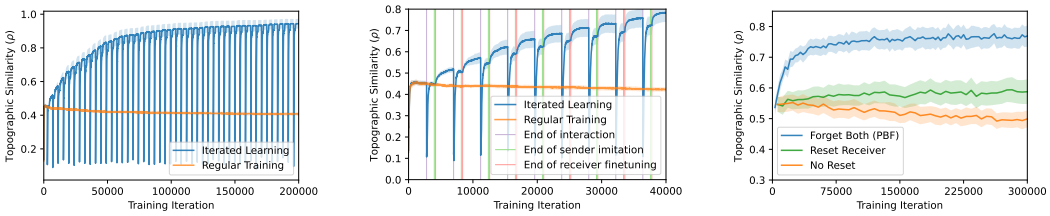
To test hypothesis 1, we freeze the early layer after the initial training generation and reinitialize the later layers for retraining in subsequent generations. If the later layers improve as a result of learning on top of well-developed early layer features, we should expect a performance improvement during relearning even when early layers are frozen. As shown in Figure 3c under "freeze early layers", we observe no significant performance improvement in this setting, suggesting that simply relearning later layers has little effect on generalization performance.

To test hypothesis 2, we design a reverse experiment where the later layers (except for the output FC layer) are reinitialized and *then* frozen at each subsequent relearning generation. The early layers are trained continuously in each generation. As shown in Figure 3c under "freeze later layers", we find that even with a random frozen layer in the middle, iterative retraining of the early layers still improves performance significantly, even matching normal LLF training in this case. To test the interpretation that early layers improve through learning under different conditions, we perform the same experiment as before, except we keep the later layers frozen at the same initialization in each generation. This reduces the amount of variability seen during iterative retraining. As shown in Figure 3c under "freeze fixed later layers", we find the performance of this to be much worse than the version with a different reinitialization each generation, demonstrating the importance of having variable conditions for relearning. These analyses suggest that the main function of iterative retraining is to distill features from the unforgotten knowledge that are consistently useful under different learning conditions.

5.2 Compositionality

The analysis in Section 5.1 supports the hypothesis that features that are consistently learned across generations are strengthened in the iterative retraining process. If this hypothesis explains why iterative algorithms improve compositionality in the Lewis game, it would predict that (i) compositional mappings are consistently learned across generations, (ii) the compositional mapping is strengthened during repeated retraining, and (iii) ρ increases during the retraining stage.

For IL, Ren et al. (2020) show that by limiting the number of training iterations in the imitation phase, the new sender can learn a language with better ρ than the previous one, arguing that the compositional components of the language are learned first. The success of IL has primarily been attributed to this increase in compositionality during the imitation phase, which follows the explanation in the cognitive science theories from which IL derives (Kirby, 2001). However, when viewed



(a) Iterated learning.

(b) Iterated learning, zoomed to the first 40000 steps.

(c) Ease-of-teaching.

Figure 4: Topographic similarity (ρ) in the Lewis game with different forms of forgetting. (a) presents the ρ across all phases of iterated learning; (b) zooms into the first 40000 steps to illustrate that ρ improves in two stages for every generation: first during reinitialization and imitation (forget), but it is generally during interaction that the sender starts outperforming the previous generation's ρ (relearn). (c) plots ρ at the end of each generation for the ease-of-teaching setting.

as an instance of forget-and-relearn, our hypothesis predicts that the improved performance in IL is primarily driven by the interaction (retraining) phase. The retraining phase reinforces features that are consistently learned, and we conjecture that these correspond to the compositional mappings. We show in Figure 4b that the interaction phase is indeed primarily responsible for the improvement in ρ. By looking at ρ during both the imitation and interaction phases using optimal hyperparameters under the setting in Ren et al. (2020), we see that increases in ρ occur during the interaction phase, while the optimal imitation phase does not even need to result in a higher ρ than the end of the previous generation.

To show that the compositional components of the language are repeatedly learned and strengthened during retraining, we visualize the learned mappings from each input dimension to message dimension in Appendix A4. We see that the same compositional mappings are retained across generations while the non-compositional aspects fluctuate and decrease in magnitude. We also observe that the probability of compositional mappings increase with increasing number of generations, illustrating the strengthening effects of iterative retraining.

6 Conclusion

We introduce *forget-and-relearn* as a general framework to unify a number of seemingly disparate iterative algorithms in the literature. Our work reveals several insights into what makes iterative training a successful paradigm. We show that various forms of weight perturbation, commonly found in iterative algorithms, disproportionately forget undesirable information. We hypothesize that this is a key factor to the success of these algorithms, and support this conjecture by showing that how well we can selectively forget undesirable information corresponds to the performance of the resulting algorithms. Although we focus discussion on the forgetting of undesirable information, our analysis in Section 5 implies that this is in service of preserving desirable information. We demonstrate that the relearning stage amplifies the unforgotten information, and distills from it features that are consistently useful under different initial conditions induced by the forgetting step.

This work has implications in understanding and designing new iterative algorithms. It places emphasis on *what is forgotten* rather than what is learned, and demonstrates that designing new methods for targeted information removal can be a fruitful area of research. It can often be easier to define and suppress unwanted behavior than to delineate good behavior, and we illustrate two ways of doing so. Our results suggest that there exists a *Goldilocks zone of forgetting*. Forget too little and the network could easily retrain to the same basin; forget too much and the network would fail to accumulate progress over multiple relearning rounds. Where this zone lies raises interesting questions in our understanding of neural network training that can be explored in future work. Finally, the idea that features that are consistently useful under different learning conditions is reminiscent of the line of work in invariant predictions (Arjovsky et al., 2020; Mitrovic et al., 2020; Zhang et al., 2021; Parascandolo et al., 2020). Understanding this dynamic in the iterative regime may point the way to creating algorithms that capture the same benefit without the expensive iterative training process.

REFERENCES

Ibrahim Alabdulmohsin, Hartmut Maennel, and Daniel Keysers. The impact of reinitialization on generalization in convolutional neural networks, 2021.

Zeyuan Allen-Zhu and Yuanzhi Li. Towards understanding ensemble, knowledge distillation and self-distillation in deep learning. *arXiv preprint arXiv:2012.09816*, 2020.

Martin Arjovsky, Léon Bottou, Ishaan Gulrajani, and David Lopez-Paz. Invariant risk minimization, 2020.

Sanjeev Arora, Rong Ge, Behnam Neyshabur, and Yi Zhang. Stronger generalization bounds for deep nets via a compression approach, 2018.

Devansh Arpit, Stanislaw Jastrzebski, Nicolas Ballas, David Krueger, Emmanuel Bengio, Maxinder S. Kanwal, Tegan Maharaj, Asja Fischer, Aaron Courville, Yoshua Bengio, and Simon Lacoste-Julien. A closer look at memorization in deep networks, 2017.

Robert J. N. Baldock, Hartmut Maennel, and Behnam Neyshabur. Deep learning through the lens of example difficulty, 2021.

Jeffrey Barrett and Kevin Zollman. The role of forgetting in the evolution and learning of language. *J. Exp. Theor. Artif. Intell.*, 21:293–309, 12 2009.

Robert A. Bjork and Ted W. Allen. The spacing effect: Consolidation or differential encoding? *Journal of Verbal Learning and Verbal Behavior*, 9(5):567–572, 1970.

Robert A. Bjork and Elizabeth L. Bjork. Forgetting as the friend of learning: implications for teaching and self-regulated learning. *Advances in Physiology Education*, 2019.

Henry Brighton and Simon Kirby. Understanding linguistic evolution by visualizing the emergence of topographic mappings. *Artificial life*, 12(2):229–242, 2006.

Vitaly Feldman and Chiyuan Zhang. What neural networks memorize and why: Discovering the long tail via influence estimation, 2020.

Jakob Foerster, Ioannis Alexandros Assael, Nando De Freitas, and Shimon Whiteson. Learning to communicate with deep multi-agent reinforcement learning. In *Advances in neural information processing systems*, pp. 2137–2145, 2016.

Pierre Foret, Ariel Kleiner, Hossein Mobahi, and Behnam Neyshabur. Sharpness-aware minimization for efficiently improving generalization, 2021.

Jonathan Frankle and Michael Carbin. The lottery ticket hypothesis: Training pruned neural networks. *CoRR*, 2018.

Jonathan Frankle, Gintare Karolina Dziugaite, Daniel M. Roy, and Michael Carbin. The lottery ticket hypothesis at scale. *CoRR*, 2019.

Robert M. French. Catastrophic forgetting in connectionist networks. *Trends in Cognitive Sciences*, 1999.

Tommaso Furlanello, Zachary C. Lipton, Michael Tschannen, Laurent Itti, and Anima Anandkumar. Born again neural networks, 2018.

Robert Geirhos, Jörn-Henrik Jacobsen, Claudio Michaelis, Richard Zemel, Wieland Brendel, Matthias Bethge, and Felix A. Wichmann. Shortcut learning in deep neural networks. *Nature Machine Intelligence*, 2020.

Lauren Gravitz. The importance of forgetting. *Nature*, 571(July):S12–S14, 2019.

Kaiming He, Xiangyu Zhang, Shaoqing Ren, and Jian Sun. Deep residual learning for image recognition, 2015.

Cong Duy Vu Hoang, Philipp Koehn, Gholamreza Haffari, and Trevor Cohn. Iterative back-translation for neural machine translation. In *NMT@ACL*, 2018.

Sepp Hochreiter and Jürgen Schmidhuber. Long short-term memory. *Neural Computation*, 9(8): 1735–1780, 1997.

Sara Hooker, Aaron Courville, Gregory Clark, Yann Dauphin, and Andrea Frome. What do compressed deep neural networks forget?, 2021.

Gao Huang, Zhuang Liu, Laurens van der Maaten, and Kilian Q. Weinberger. Densely connected convolutional networks, 2018.

Eric Jang, Shixiang Gu, and Ben Poole. Categorical reparameterization with gumbel-softmax, 2017.

Yiding Jiang, Behnam Neyshabur, Hossein Mobahi, Dilip Krishnan, and Samy Bengio. Fantastic generalization measures and where to find them, 2019.

Aditya Khosla, Nityananda Jayadevaprakash, Bangpeng Yao, and Li Fei-Fei. Novel dataset for fine-grained image categorization : Stanford dogs. 2012.

Diederik P. Kingma and Jimmy Ba. Adam: A method for stochastic optimization, 2017.

Simon Kirby. Spontaneous evolution of linguistic structure-an iterated learning model of the emergence of regularity and irregularity. *IEEE Transactions on Evolutionary Computation*, 5(2):102–110, 2001.

James Kirkpatrick, Razvan Pascanu, Neil Rabinowitz, Joel Veness, Guillaume Desjardins, Andrei A Rusu, Kieran Milan, John Quan, Tiago Ramalho, Agnieszka Grabska-Barwinska, et al. Overcoming catastrophic forgetting in neural networks. *Proceedings of the national academy of sciences*, 114(13):3521–3526, 2017.

Angeliki Lazaridou, Alexander Peysakhovich, and Marco Baroni. Multi-agent cooperation and the emergence of (natural) language. *arXiv preprint arXiv:1612.07182*, 2016.

Angeliki Lazaridou, Karl Moritz Hermann, Karl Tuyls, and Stephen Clark. Emergence of linguistic communication from referential games with symbolic and pixel input. *arXiv preprint arXiv:1804.03984*, 2018.

David Lewis. *Convention: A philosophical study*. John Wiley & Sons, 2008.

Fushan Li and Michael Bowling. Ease-of-teaching and language structure from emergent communication, 2019.

Xingjian Li, Haoyi Xiong, Haozhe An, Chengzhong Xu, and Dejing Dou. Rifle: Backpropagation in depth for deep transfer learning through re-initializing the fully-connected layer, 2020.

Ilya Loshchilov and Frank Hutter. Sgdr: Stochastic gradient descent with warm restarts, 2017.

Yuchen Lu, Soumye Singhal, Florian Strub, Aaron Courville, and Olivier Pietquin. Countering language drift with seeded iterated learning. In *International Conference on Machine Learning*, pp. 6437–6447. PMLR, 2020.

Xiaolong Ma, Geng Yuan, Xuan Shen, Tianlong Chen, Xuxi Chen, Xiaohan Chen, Ning Liu, Minghai Qin, Sijia Liu, Zhangyang Wang, and Yanzhi Wang. Sanity checks for lottery tickets: Does your winning ticket really win the jackpot?, 2021.

Chris J. Maddison, Andriy Mnih, and Yee Whye Teh. The concrete distribution: A continuous relaxation of discrete random variables, 2017.

Subhransu Maji, Esa Rahtu, Juho Kannala, Matthew Blaschko, and Andrea Vedaldi. Fine-grained visual classification of aircraft, 2013.

Michael McCloskey and Neal J Cohen. Catastrophic interference in connectionist networks: The sequential learning problem. In *Psychology of learning and motivation*, volume 24, pp. 109–165. Elsevier, 1989.

Jovana Mitrovic, Brian McWilliams, Jacob Walker, Lars Buesing, and Charles Blundell. Representation learning via invariant causal mechanisms, 2020.

Rafael Müller, Simon Kornblith, and Geoffrey Hinton. When does label smoothing help?, 2019.

Preetum Nakkiran, Gal Kaplun, Dimitris Kalimeris, Tristan Yang, Benjamin L. Edelman, Fred Zhang, and Boaz Barak. Sgd on neural networks learns functions of increasing complexity, 2019.

Maria-Elena Nilsback and Andrew Zisserman. Automated flower classification over a large number of classes. In *2008 Sixth Indian Conference on Computer Vision, Graphics Image Processing*, pp. 722–729, 2008. doi: 10.1109/ICVGIP.2008.47.

Giambattista Parascandolo, Alexander Neitz, Antonio Orvieto, Luigi Gresele, and Bernhard Schölkopf. Learning explanations that are hard to vary, 2020.

Mary Phuong and Christoph Lampert. Towards understanding knowledge distillation. In *International Conference on Machine Learning*, pp. 5142–5151. PMLR, 2019.

Ariadna Quattoni and Antonio Torralba. Recognizing indoor scenes. In *2009 IEEE Conference on Computer Vision and Pattern Recognition*, pp. 413–420, 2009. doi: 10.1109/CVPR.2009.5206537.

Roger Ratcliff. Connectionist models of recognition memory: constraints imposed by learning and forgetting functions. *Psychological review*, 97(2):285, 1990.

Yi Ren, Shangmin Guo, Matthieu Labeau, Shay B. Cohen, and Simon Kirby. Compositional languages emerge in a neural iterated learning model. In *International Conference on Learning Representations*, 2020.

Anthony Robins. Catastrophic forgetting, rehearsal and pseudorehearsal. *Connection Science*, 7(2): 123–146, 1995.

Joan Serra, Didac Suris, Marius Miron, and Alexandros Karatzoglou. Overcoming catastrophic forgetting with hard attention to the task. In *International Conference on Machine Learning*, pp. 4548–4557. PMLR, 2018.

Ravid Shwartz-Ziv and Naftali Tishby. Opening the black box of deep neural networks via information. *arXiv preprint arXiv:1703.00810*, 2017.

Samuel Stanton, Pavel Izmailov, Polina Kirichenko, Alexander A Alemi, and Andrew Gordon Wilson. Does knowledge distillation really work? *arXiv preprint arXiv:2106.05945*, 2021.

Christian Szegedy, Vincent Vanhoucke, Sergey Ioffe, Jonathon Shlens, and Zbigniew Wojna. Rethinking the inception architecture for computer vision, 2015.

Ahmed Taha, Abhinav Shrivastava, and Larry Davis. Knowledge evolution in neural networks, 2021.

Jiaxi Tang, Rakesh Shivanna, Zhe Zhao, Dong Lin, Anima Singh, Ed H Chi, and Sagar Jain. Understanding and improving knowledge distillation. *arXiv preprint arXiv:2002.03532*, 2020.

Guillermo Valle-Pérez, Chico Q. Camargo, and Ard A. Louis. Deep learning generalizes because the parameter-function map is biased towards simple functions. In *International Conference on Learning Representations*, 2019.

Ankit Vani, Max Schwarzer, Yuchen Lu, Eeshan Dhekane, and Aaron Courville. Iterated learning for emergent systematicity in VQA. In *International Conference on Learning Representations*, 2021.

C. Wah, S. Branson, P. Welinder, P. Perona, and S. Belongie. The Caltech-UCSD Birds-200-2011 Dataset. Technical Report CNS-TR-2011-001, California Institute of Technology, 2011.

Chao Wang, Huimin Yue, Zhechun Hu, Yuwen Shen, Jiao Ma, Jie Li, Xiao-Dong Wang, Liang Wang, Binggui Sun, Peng Shi, Lang Wang, and Yan Gu. Microglia mediate forgetting via complement-dependent synaptic elimination. *Science*, 2020.

Ronald J. Williams. Simple statistical gradient-following algorithms for connectionist reinforcement learning. *Machine Learning*, 8(3):229–256, 1992.

Qizhe Xie, Minh-Thang Luong, Eduard Hovy, and Quoc V. Le. Self-training with noisy student improves imagenet classification, 2019.

Jason Yosinski, Jeff Clune, Yoshua Bengio, and Hod Lipson. How transferable are features in deep neural networks?, 2014.

Sukmin Yun, Jongjin Park, Kimin Lee, and Jinwoo Shin. Regularizing class-wise predictions via self-knowledge distillation, 2020.

Dinghuai Zhang, Kartik Ahuja, Yilun Xu, Yisen Wang, and Aaron Courville. Can subnetwork structure be the key to out-of-distribution generalization?, 2021.

Hattie Zhou, Janice Lan, Rosanne Liu, and Jason Yosinski. Deconstructing lottery tickets: Zeros, signs, and the supermask. 2019a.

Wenda Zhou, Victor Veitch, Morgane Austern, Ryan P. Adams, and Peter Orbanz. Non-vacuous generalization bounds at the imagenet scale: A pac-bayesian compression approach, 2019b.

A APPENDIX

A1 PARTIAL WEIGHT PERTURBATION AS TARGETED FORGETTING

A1.1 DETAILS ON WEIGHT PERTURBATION METHODS

We can categorize this class of forgetting method in terms of both a *mask criteria* and a *mask action*. The mask criteria is a function $m : \mathbb{R}^d \to \{0, 1\}^d$, which determines which weights will be changed during the forgetting step by producing a binary mask with the same dimensions as the parameters of the neural network. The mask action $s : \mathbb{R}^d \to \mathbb{R}^d$ determines how the replacement values of the weights are computed. The mask-1 action s_1 operates on weights with mask value 1, and mask-0 action s_0 operates on weights with mask value 0. For a neural network parameterized by $\mathbf{\Theta}$, forgetting through partial weight perturbation can then be defined by the update rule

$$\mathbf{\Theta} \leftarrow m(\mathbf{\Theta}) \odot s_1(\mathbf{\Theta}) + (1 - m(\mathbf{\Theta})) \odot s_0(\mathbf{\Theta}). \tag{2}$$

Table A1: Types of weight perturbations for image classification experiments. Random mask criteria means that masks are generated randomly, and IMP-style mask criteria equals to 1 for corresponding weights with large final magnitudes. Mask-1 Action refers to the operation on weights with corresponding mask value of 1, and Mask-0 Action refers to the operation on weights with corresponding mask value of 0.

Method	**Mask Criteria**	**Mask-1 Action**	**Mask-0 Action**
KE-style Random Reinit	Random	Identity	Reinitialize
IMP-style Weight Rewind	$\lvert\mathbf{\Theta}_{final}\rvert$	Rewind	Set to 0

Table A2: A example of a compositional language adopted from Li & Bowling (2019).

	black	blue	green	grey	pink	purple	red	yellow
circle	bc	lc	gc	rc	pc	uc	dc	yc
square	bs	ls	gs	rs	ps	us	ds	ys
star	ba	la	ga	ra	pa	ua	da	ya
triangle	bt	lt	gt	rt	pt	ut	dt	yt

Table A3: A example of a non-compositional language adopted from Li & Bowling (2019).

	black	blue	green	grey	pink	purple	red	yellow
circle	ys	gc	lc	pa	bc	ut	ua	rs
square	ga	la	yc	ra	dc	pt	rc	dt
star	yt	ls	ba	bs	bt	lt	uc	gs
triangle	pc	ps	da	ds	rt	us	ya	gt

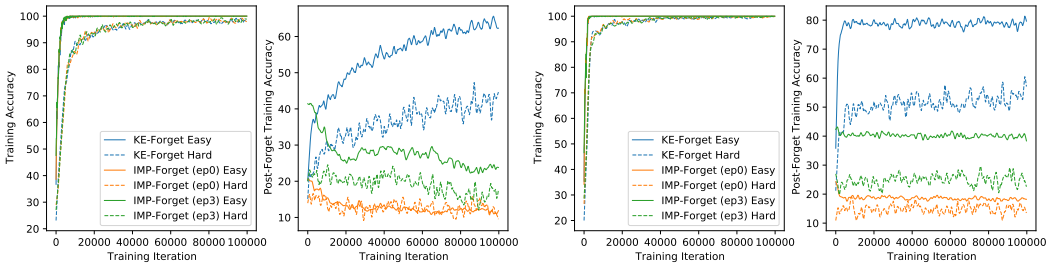
A1.2 EXTENSION TO CIFAR-10 AND IMAGENET

We extend our analyses of partial weight perturbation to CIFAR-10 on a 4-layer convolutional model (Conv4) and a ResNet18 model, and ImageNet on ResNet50. All CIFAR models are evaluated using a 50% reset rate. We find reliable trends for both KE-style and IMP-style forgetting for all datasets.

For CIFAR-10, we follow the exact same procedure as the MNIST experiments. Following the setup in Frankle & Carbin (2018), Conv4 model is trained using the Adam optimizer, and ResNet18 is trained using SGD. Results on easy and hard examples are shown in Figure A1. We find that KE-style forgetting results in consistent and significant difference between easy and hard examples.

Table A4: Types of weight perturbations for compositionality experiments. Random mask criteria means that masks are generated randomly, and weight mask criteria equals to 1 for corresponding weights with large final magnitudes. Frequency indicates how often masks are resampled. Mask-1 Action refers to the operation on weights with corresponding mask value of 1, and Mask-0 Action refers to the operation on weights with corresponding mask value of 0.

Method	Mask Criteria	Frequency	Mask-1 Action	Mask-0 Action
Random Reinit	Random	Per Iter	Identity	Reinitialize
Random Zero	Random	Per Iter	Identity	Set to 0
Same Weight Reinit	$\lvert\boldsymbol{\Theta}_{init}\rvert$	Once	Identity	Reinitialize
Same Weight Zero	$\lvert\boldsymbol{\Theta}_{init}\rvert$	Once	Identity	Set to 0



(a) Conv4 on CIFAR-10

(b) ResNet18 on CIFAR-10

Figure A1: The left panels in (a) and (b) show training accuracy of easy and hard example groups for different types of weight perturbation. The right panels in (a) and (b) show the accuracy of each example group for the same model with weight perturbation applied. Same colors represent the same forgetting operation, and dashed lines represent the accuracy on the hard examples. Results are averaged over 5 runs.

However, the IMP-style forgetting operation CIFAR-10 models renders the post forgetting accuracy close to chance, and there is only a small difference between easy and hard example groups. In the lottery ticket literature, it has long been observed that "late resetting" is needed to get performant sparse models as datasets and models get larger (Frankle et al., 2019). In late resetting, we would rewind kept weights to the value a few epochs after training, rather than to the initial untrained values. We perform a variant of IMP-style forgetting where weights are rewound to epoch 3. We find that IMP-style forgetting with late resetting significantly increases accuracy for both groups, and much more so for the easy group than the hard group. These results demonstrate that IMP with late resetting achieves more targeted forgetting of undesirable information. These observations suggest another possible reason for the increased performance when using late resetting: IMP with late resetting better leverages the benefits of forget-and-relearn.

For ImageNet experiments, given computational constraints, we use a pretrained ResNet50 model on ImageNet and separate examples into easy and hard groups based on output margin. We only use training examples that are correctly classified as to not disadvantage the difficult examples. This means that both group has 100% accuracy pre-forgetting. We then perform various forgetting operations on top of the pretrained model and measure the accuracy of the two groups post-forgetting. For KE-style forgetting, we randomly reinitialize 20% of weights on the same pretrained model and aggregate results over 5 samples. For IMP-style forgetting, we set varying percentages of small weights to zero as a proxy given we are using a pretrained model and do not have access to initial or intermediate weights. Results are shown in Table A5, and we find that hard examples are more severely affected in all cases.

Table A5: Weight perturbations on ResNet50 for ImageNet. Using a pretrained model, we filter out the ImageNet training examples that are wrongly classified by the pretrained model. Hard examples are the 10% of remaining training examples with the largest output margin, and easy examples are the remaining training examples. We measure the accuracy of the two groups after performing various forgetting operations on the pretrained models. Random reinit values are the mean and standard error over 5 samples.

Method	**Easy Example Accuracy**	**Hard Example Accuracy**
Random Reinit 20% of Weights	$45.6\% \pm 0.7\%$	$17.9\% \pm 0.3\%$
Set Small Weights to Zero (50%)	89.8%	47.3%
Set Small Weights to Zero (40%)	97.9%	65.5%
Set Small Weights to Zero (30%)	99.7%	80.1%
Set Small Weights to Zero (20%)	100%	90.3%

A2 Targeted Forgetting Improves Performance

A2.1 Architectures and Training Details

All networks are trained with stochastic gradient descent (SGD) with momentum of 0.9 and weight decay of 10^{-4}. We also use a cosine learning rate schedule (Loshchilov & Hutter, 2017). Taha et al. (2021) use an initial learning rate of 0.256, but we find that a smaller learning rate than what is used in Taha et al. (2021) to be beneficial for certain datasets, thus we consider a learning rate in $\{0.1, 0.256\}$ for all experiments and report the setting with the better validation performance. Models are trained with a batch size of 32 for 200 epochs each generation. No early stopping is used.

All ResNet18 models use a default layer threshold of 10 (start of block 3), except for the Flower dataset which has been tuned on the provided validation set and use a threshold of 14 (start of block 4) on the SMTH experiments. All DenseNet169 models use a default layer threshold of 40 (start of denseblock 3), except for the Aircraft dataset which has been tuned on the provided validation set and use a threshold of 68 (middle of denseblock 3).

A2.2 Dataset Summary

Table A6: Summary of the five datasets used in Section 4.1, adopted from Taha et al. (2021).

	Classes	Train Size	Val Size	Test Size	Total Size
Flower (Nilsback & Zisserman, 2008)	102	1020	1020	6149	8189
CUB (Wah et al., 2011)	200	5994	N/A	5794	11788
Aircraft (Maji et al., 2013)	100	3334	3333	3333	10000
MIT67 (Quattoni & Torralba, 2009)	67	5360	N/A	1340	6700
Stanford-Dogs (Khosla et al., 2012)	120	12000	N/A	8580	20580

Taha et al. (2021) uses different resizing of images for different datasets, and the specific resizing parameters are not specified in the paper. For consistency, we resize all datasets to $(256, 256)$. We use a validation split to tune hyperparameters and report results on the test set when available.

A2.3 Extension to Larger Datasets and Models

In this section, we evaluate LLF on larger datasets and models than what was used in the core comparison with KE. We train ResNet50 on Tiny-ImageNet, which consists of 200 classes with 500 training examples each. We use Tiny-ImageNet as a large scale dataset that still suffers from a small number of training examples. We adopt the training setup from Ma et al. (2021) and set $L = 23$ (first layer of the third residual block). Results are shown in Table A7. We find a significant gain

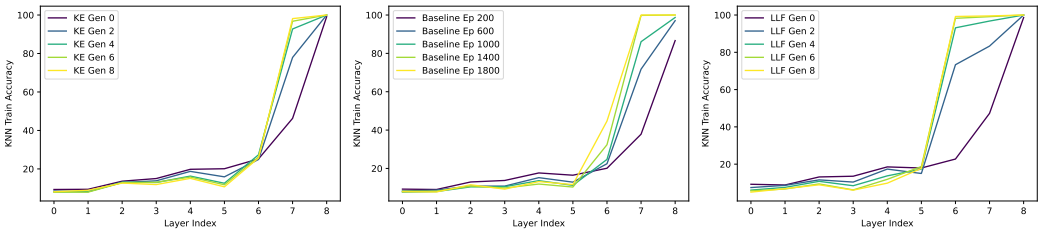
Table A7: Later Layer Forgetting on CIFAR-10, CIFAR-100, and Tiny-ImageNet. Results are averaged over 3 runs and reported for hyperparameter settings with best validation performance. N3 and N10 indicate the additional number of training generations on top of the baseline model. The long baseline scales the step LR schedule based on the additional epochs.

Method	CIFAR-100	CIFAR-10	Tiny-ImageNet
Smth (N1)	-	-	54.37
Smth long (N3)	-	-	51.16
Smth + LLF (N3) **(Ours)**	**-**	**-**	**56.12**
Smth long (N10)	-	-	49.27
Smth + LLF (N10) **(Ours)**	**-**	**-**	**56.92**

over the baseline on Tiny-ImageNet. At the time of this rebuttal draft, we are still pending results on CIFAR-10.

A2.4 Comparison to LW

Concurrent work (Alabdulmohsin et al., 2021) studies various types of iterative reinitialization approaches and finds that reinitializing entire layers produced the best performance. They propose a layer-wise reinitialization scheme, proceeding from bottom to top and reinitializing one fewer layer each generation. In addition, Alabdulmohsin et al. (2021) performs weight rescaling and activation normalization for each layer that is not reinitialized. We refer to this method as LW and add a comparison to their method in Table 1. We find that LLF outperforms LW across all datasets we consider. However, we note that LLF introduces an additional hyperparameter for the layer threshold, which LW does not require. Additionally, we find that under our experimental settings, several choices proposed in LW actually harms performance. We remove the addition of weight rescaling and normalization, and do not reinitialize batchnorm parameters, in order to achieve the best performance under the LW schedule. The forget-and-relearn hypothesis suggests that it is unnecessary to reinitialize the first few layers. Doing so in LW hinders their progress in the first few generations of training, and also leads to poorer generalization performance even after completing the full sequential schedule.



(a) KNN probe for KE. (b) KNN probe for Long Baseline. (c) KNN probe for LLF.

Figure A2: KNN probe train accuracy for various ResNet18 models trained on Flower. The layers shown are the end of each block and after the softmax operation. We use K=3 to compute accuracy using the activations from each layer. The different curves in each panel show that overall prediction depth (as approximated by average KNN accuracy across layers) decreases with more training. LLF in (c) shows the most significant change, with the KNN probe performing near perfect at layer 6, which is earlier than the other two methods.

A3 Details on Partial Balanced Forgetting

Our experimental settings follows Li & Bowling (2019). We use one-layer LSTMs with a hidden size of 100 to parameterize both the sender and receiver agents. We train using batch size of 100, and use the Adam optimizer (Kingma & Ba, 2017) with a learning rate of 0.001. The language

Table A8: Comparing KE and Later Layer Forgetting for ResNet18. Results are averaged over 3 runs and reported for hyperparameter settings with best validation performance. KE experiments use KELS split with a split rate of 0.8. LLF uses $L \in \{10, 14\}$, corresponding to block 3 and 4 in ResNet18. N3, N8, N10 indicate the additional number of training generations on top of the baseline model. LLF consistently outperforms all other methods.

Method	Flower	CUB	Aircraft	MIT	Dog
Smth (N1)	51.02	58.92	57.16	56.04	63.64
Smth long (N3)	59.51	66.03	62.55	59.53	65.39
Smth + KE (N3)	57.95	63.49	60.56	58.78	64.23
Smth + LLF (N3) **(Ours)**	**63.52**	**70.76**	**68.88**	**63.28**	**67.54**
Smth long (N10)	66.89	70.50	65.29	61.29	66.19
Smth + KE (N10)	63.25	66.51	63.32	59.58	63.86
Smth + LLF (N10) **(Ours)**	**70.87**	**72.47**	**70.82**	**64.40**	**68.51**
Smth + LW (N8)	62.84	70.58	67.36	61.24	66.58
Smth + LW NoNorm NoRescale (N8)	65.97	71.15	67.97	63.13	66.96
Smth + LW(-BN) (N8)	63.67	70.10	66.79	60.10	-
Smth + LW(-BN) NoNorm NoRescale (N8)	68.43	70.87	69.10	61.67	66.97
Smth + LLF (N8) **(Ours)**	**69.48**	**72.30**	**70.37**	**63.58**	**68.45**
CS-KD (N1)	57.57	66.61	65.18	58.61	66.48
CS-KD long (N3)	64.44	69.50	65.23	57.16	66.43
CS-KD + KE (N3)	63.48	68.76	67.16	58.88	67.05
CS-KD + LLF (N3) **(Ours)**	**67.20**	**72.58**	**71.65**	**62.41**	**68.77**
CS-KD long (N10)	68.68	69.59	64.58	56.12	64.96
CS-KD + KE (N10)	67.29	69.54	68.70	57.61	67.11
CS-KD + LLF (N10) **(Ours)**	**74.68**	**73.51**	**72.01**	**62.89**	**69.20**
CS-KD + LW (N8)	65.80	70.94	66.37	57.96	66.74
CS-KD + LW NoNorm NoRescale (N8)	69.96	70.91	69.53	60.22	67.47
CS-KD + LW(-BN) (N8)	69.54	-	68.87	-	-
CS-KD + LW(-BN) NoNorm NoRescale (N8)	**73.72**	71.81	70.82	59.18	68.09
CS-KD + LLF (N8) **(Ours)**	73.48	**73.47**	**71.95**	**62.26**	**69.24**

contains a vocabulary size of 8 and a message length of 2. We use 4 SHAPE and 8 COLOR attributes, and the object set consist of all 32 combinations of these attributes.

The agents are trained with REINFORCE and entropy regularization using the following objectives:

$$\nabla_{\theta^S} J = \mathbb{E}_{\pi^S, \pi^R}[R(\hat{t}, t) \cdot \nabla_{\theta^S} \log \pi^S(m \mid t)] + \lambda^S \cdot \nabla_{\theta^S} H[\pi^S(m \mid t)]$$

$$\nabla_{\theta^R} J = \mathbb{E}_{\pi^S, \pi^R}[R(\hat{t}, t) \cdot \nabla_{\theta^R} \log \pi^R(\hat{t} \mid m, c)] + \lambda^R \cdot \nabla_{\theta^R} H[\pi^R(\hat{t} \mid m, c)]$$

We use $\lambda^S = 0.1$ and $\lambda^R = 0.1$ in all our experiments, which differs slightly from Li & Bowling (2019) that use $\lambda^R = 0.05$, however we observe that the difference is small between these settings. We train the "no reset" and "reset receiver" baselines for 6000 iterations per generation for 50 generations, following the hyperparameters in Li & Bowling (2019). We train our PBF method with "same weight reinit" for 3000 iterations per generation for 100 generations for best performance. However we note that even using the same 50 generation hyperparameter, PBF significantly outperforms its baselines.

Table A9: Comparing KE and Later Layer Forgetting for DenseNet169. Results are averaged over 3 runs and reported for hyperparameter settings with best validation performance. KE experiments use WELS split with a split rate of 0.7. LLF uses $L \in \{40, 68\}$. N3, N8, N10 indicate the additional number of training generations on top of the baseline model. LLF consistently outperforms all other methods.

Method	Flower	CUB	Aircraft	MIT	Dog
Smth (N1)	45.87	61.59	58.06	57.21	66.46
Smth long (N3)	59.39	70.87	67.55	62.29	68.82
Smth + KE (N3)	58.35	68.85	65.63	60.35	68.64
Smth + LLF (N3) **(Ours)**	**62.31**	**71.97**	**70.53**	**64.60**	**70.19**
Smth long (N10)	67.47	71.98	70.69	60.72	67.48
Smth + KE (N10)	65.19	70.20	67.47	60.77	68.62
Smth + LLF (N10) **(Ours)**	**70.09**	**73.12**	**74.31**	**61.69**	**69.93**
CS-KD (N1)	52.95	64.28	64.87	57.61	66.90
CS-KD long (N3)	60.03	63.80	67.68	57.21	67.01
CS-KD + KE (N3)	63.33	66.78	68.47	58.81	68.49
CS-KD + LLF (N3) **(Ours)**	**65.43**	**73.54**	**72.22**	**61.74**	**70.61**
CS-KD long (N10)	63.84	63.58	67.22	55.49	64.69
CS-KD + KE (N10)	69.24	66.34	69.51	58.33	67.73
CS-KD + LLF (N10) **(Ours)**	**72.23**	**74.20**	**73.30**	**63.18**	**71.07**

A4 EMERGENT LANGUAGE VISUALIZATIONS

In this section, we aim to visualize the languages learned by the sender in a Lewis game in the settings of Ren et al. (2020) and Li & Bowling (2019). Despite all the runs having near-perfect training accuracy , the degree of compositionality exhibited by the emergent languages varies significantly depending on the use of forget-and-retrain as evident in Figure 4. In both these settings, each object has two attributes that can take values in $\mathcal{A}_1 = \{1, \ldots, r_1\}$ and $\mathcal{A}_2 = \{1, \ldots, r_2\}$ respectively, and each message has two tokens that can take values in $\mathcal{M}_1 = \{1, \ldots, s_1\}$ and $\mathcal{M}_2 = \{1, \ldots, s_2\}$ respectively. Let us represent $a_i^{(j)}$ as 1 if attribute i has the value j, and 0 otherwise. Similarly, we represent $m_i^{(j)}$ as 1 if message token i has the value j, and 0 otherwise. When $r_1 + r_2 = s_1 + s_2$ (*i.e.* the total number of input attribute values is equal to the total number of message token values), a compositional language with maximum topographic similarity (ρ) would have each input attribute activation $a_k^{(l)}$ mapped to a unique message token activation $m_p^{(q)}$.

Thus, we can represent the inputs and the messages both as concatenations of two one-hot vectors $\boldsymbol{a} = \{a_1^{(1)}, \ldots, a_1^{(r_1)}, a_2^{(1)}, \ldots, a_2^{(r_2)}\}$ and $\boldsymbol{m} = \{m_1^{(1)}, \ldots, m_1^{(s_1)}, m_2^{(1)}, \ldots, m_2^{(s_2)}\}$ respectively. In Figures A3-A7, we illustrate the mappings from input dimensions $\boldsymbol{a}$ to message dimensions $\boldsymbol{m}$. Visualized values closer to 1 indicate a more consistent mapping across the entire dataset, indicating a compositional mapping. Concretely, for each active input dimension $a_k^{(l)}$, we vary $\mathcal{A}_{\neq k}$ across all its values and collect the corresponding message token probabilities $\hat{\boldsymbol{m}} = \{\hat{m_1}^{(1)}, \ldots, \hat{m_1}^{(s_1)}, \hat{m_2}^{(1)}, \ldots, \hat{m_2}^{(s_2)}\}$ produced by the sender via two softmax operations. Then, the mean of these message probability vectors $\mathbb{E}_{\mathcal{A}_{\neq k}}[\hat{\boldsymbol{m}}]$ across $\mathcal{A}_{\neq k}$ is used as the row corresponding to input dimension $a_k^{(l)}$. For a perfectly compositional mapping, the visualized matrix resembles a permutation matrix.

For IL in Figure A3 and PBF in Figure A5, we see the emergence of a compositional mapping. The compositional component is retained across generations whereas the non-compositional components are disproportionately affected in the forgetting step and are more likely to get remapped. Finally, during the retraining phases, we see the compositional mappings get strengthened.

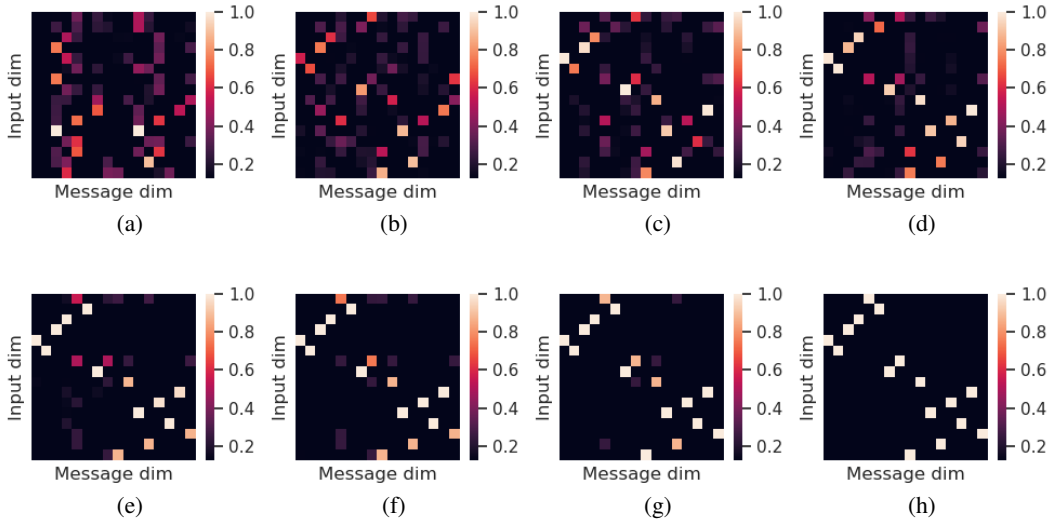


Figure A3: Mappings from input dimension to message dimension learned by the sender using **iterated learning** in the setting of Ren et al. (2020), logged after every generation for the first 32200 training iterations across all phases. A compositional language appears as a permutation matrix, where each input dimension maps to a unique message dimension.

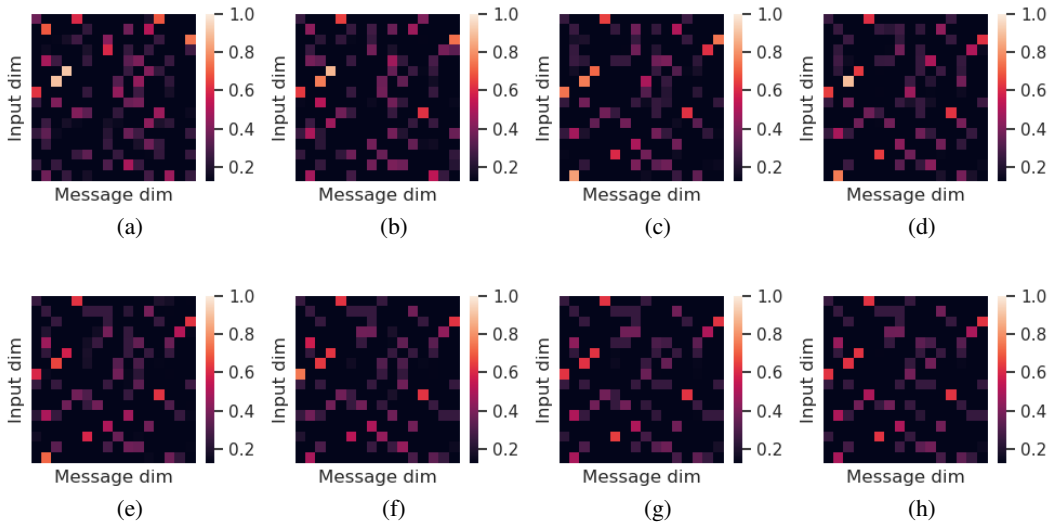


Figure A4: Mappings from input dimension to message dimension learned by the sender **without any form of forget-and-retrain** in the setting of Ren et al. (2020), logged uniformly for the first 33000 training iterations. A compositional language would have appeared as a permutation matrix, where each input dimension maps to a unique message dimension.

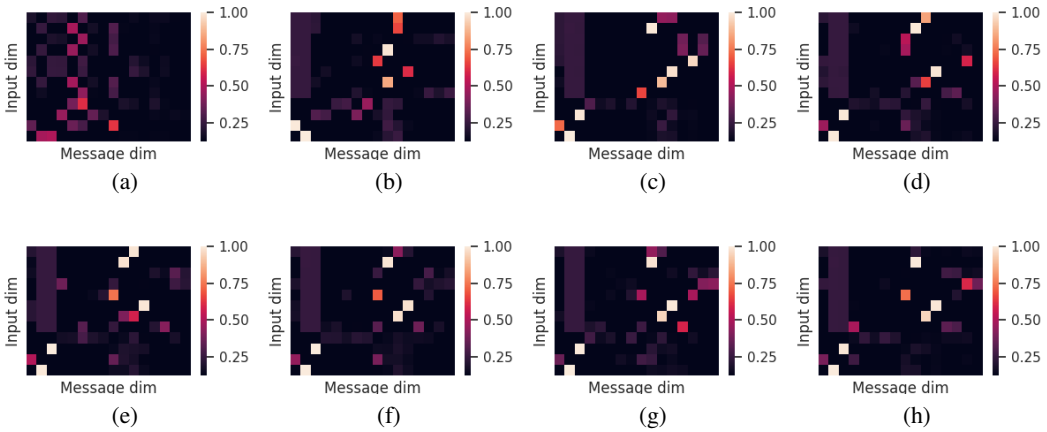


Figure A5: Mappings from input dimension to message dimension learned by the sender using **Partial Balanced Forgetting (PBF)** in the setting of Li & Bowling (2019), logged after every two generations for the first 48000 training iterations. A more compositional language has unique non-overlapping message dimension activations for different input dimensions.

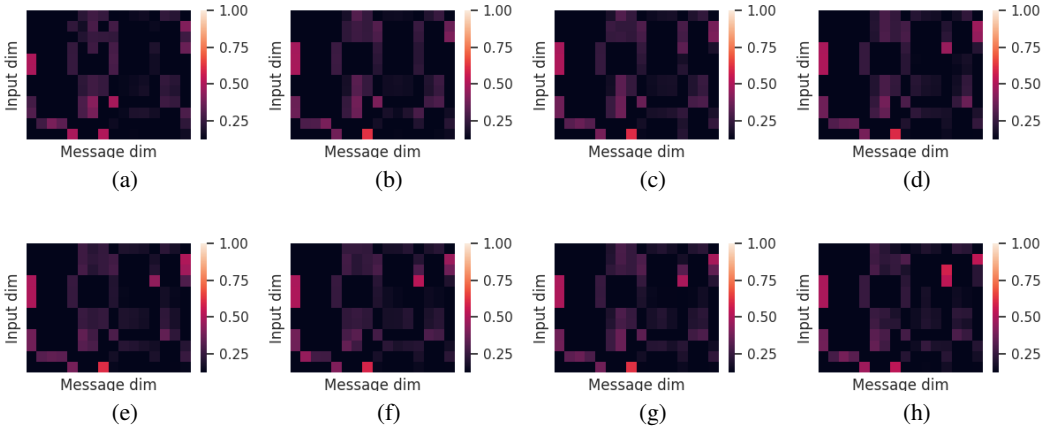


Figure A6: Mappings from input dimension to message dimension learned by the sender by **resetting the receiver periodically** following the setting of Li & Bowling (2019), logged after every generation for the first 48000 training iterations. A more compositional language has unique non-overlapping message dimension activations for different input dimensions.

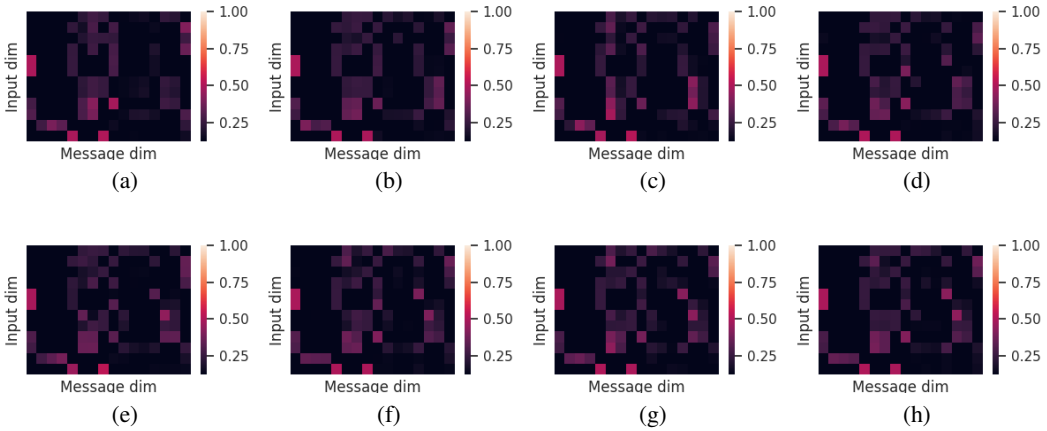


Figure A7: Mappings from input dimension to message dimension learned by the sender **without any form of forget-and-retrain** in the setting of Li & Bowling (2019), logged uniformly for the first 48000 training iterations. A more compositional language has unique non-overlapping message dimension activations for different input dimensions.

A5 Connections to Other Types of Forgetting

In the continual learning literature, catastrophic forgetting (McCloskey & Cohen, 1989; Ratcliff, 1990) refers to the decrease in performance on older tasks due to the learning of new tasks. There is a large body of literature focused on avoiding catastrophic forgetting (Ratcliff, 1990; Robins, 1995; French, 1999; Kirkpatrick et al., 2017; Serra et al., 2018). In this work, we view forgetting in a positive light, which aides learning. It is conceivable that catastrophic forgetting can even be leveraged to help learning with a well-chosen secondary task in a forget-and-relearn process.

Shwartz-Ziv & Tishby (2017) studies the progression of mutual information between each layer and the input and target variables throughout the training of deep neural networks. They reveal that the converged values lie close to the information bottleneck theoretical bound, which implies a decrease in the mutual information with the input. In a sense, the information bottleneck leads to the "forgetting" of unnecessary information. It would be interesting to explore whether there are fundamental similarities between the information loss caused by SGD training dynamics and the effect resulting from forget-and-relearn.

Barrett & Zollman (2009) studies forgetting in the Lewis game from the perspective of suboptimal equilibria. They show that using a learning rule that remembers the entire past (i.e. Herrnstein reinforcement learning), the model converges to a worse equilibrium than learning rules that discard past experience. The work further points to the possibility of designing forgetting mechanisms that are built in to the learning process itself.

Although we claim many iterative training algorithms as instances of forget-and-relearn, there are also many that we do not, even though they may be related. Algorithms like born-again networks (Furlanello et al., 2018) and self-training with noisy students (Xie et al., 2019) rely on iterative self-distillation, and do not have distinct forgetting and relearning stages. Instead, knowledge is passed to the next generation through pseudo-labels. A number of papers have tried to understand why students trained through self-distillation often generalize better than their teachers (Phuong & Lampert, 2019; Tang et al., 2020; Allen-Zhu & Li, 2020; Stanton et al., 2021); perhaps viewing these methods through the lens of forgetting undesirable information offers an alternative path.