# FORTUITOUS FORGETTING IN CONNECTIONIST NETWORKS

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## 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 (French, 1999)[1]. However, substantial evidence in psychology and neuroscience have shown that forgetting and learning have a symbiotic relationship (Bjork & Bjork, 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. One of the core problems of machine learning is the ability to generalize to unseen data. We want our models to capture generalizable concepts rather than purely statistical regularities, but these generalizable solutions are a small subset of the solution space and are often more difficult to learn naturally (Geirhos et al., 2020). In recent years, 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 part of the network while continuously training the other part. Iterative magnitude pruning (Frankle & Carbin, 2018; Frankle et al., 2019) removes weights through an iterative pruning-retraining process, and can outperform the unpruned model in certain settings. Iterative back-translation creates synthetic machine translation corpus through iterative back-translation of monolingual data (Hoang et al., 2018). Iterated learning (Ren et al., 2020)[2] passes information through a learning bottleneck, by pre-training subsequent generations of mod-

[1]The title of our work is derived from that of French (1999), titled *Catastrophic Forgetting in Connectionist Networks*.

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

els on pseudo-labeled datasets and limiting the number of training iterations. Iterated learning has been shown to improve compositionality in emergent languages (Ren et al., 2020; Vani et al., 2021) and 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 environments 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 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 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.

**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 perfor-

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

mance. At the start of each generation of training, weights in the reset-hypothesis are reinitialized, 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 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.

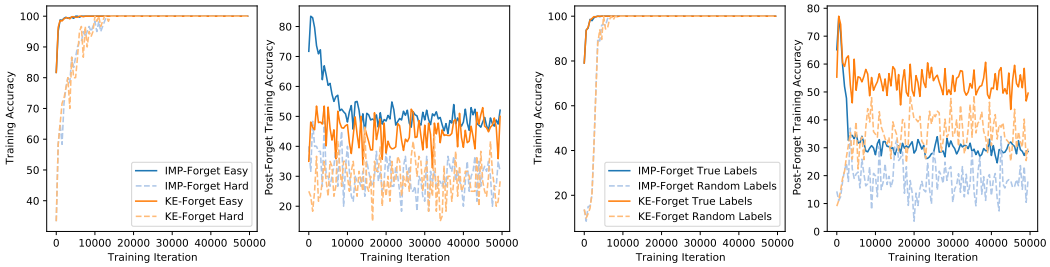
### 3.1 Image Classification

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. [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.

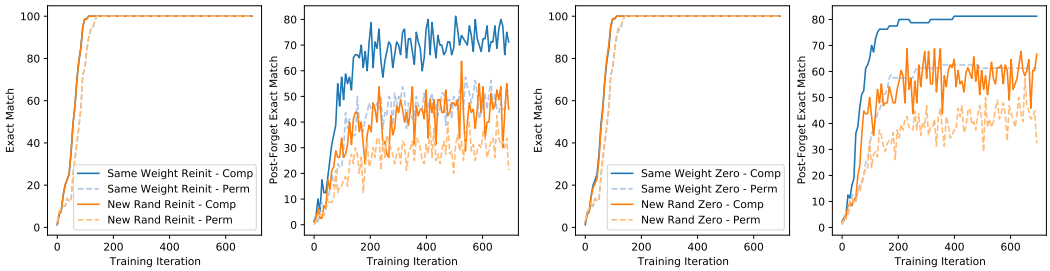
[4] We use an MLP with hidden layers 300-100-10, trained using SGD with a constant learning rate of $0.1$.

[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. Both forms of weight perturbation disproportionately affect model performance on difficult and mislabeled examples.




(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. All forms of weight perturbation disproportionately affects model performance on non-compositional language.

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 A7. We find that LLF substantially outperforms both the long baseline and the KE models across all datasets for both model architectures.

**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. Using the KE mask allows the slim fit-hypothesis to achieve comparable performance as the full network, which can be used to reduce inference cost. However, 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 A2.3.

**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 A1, 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; Ren et al., 2020), compositionality of the language is measured by topographic similarity ($\rho$), which is defined as the correlation between distances of pairs of objects in the attribute space and in the corresponding message space. Li & Bowling (2019) show that $\rho$ is higher with the ease-of-teaching approach than training without resetting the receiver.

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 and sub-optimal form of forgetting in this two-agent

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** |

system. Resetting the receiver may be reminiscent of the LLF procedure we proposed in Section 4.1, but the dynamics of this two-agent model is very different. In particular, we care about the quality of the messages, which is controlled by the sender. This motivates a balanced forgetting operation for the Lewis game, whereby both sender and receiver can forget non-compositional aspects of their shared language. Given this new understanding, 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. We also increase the frequency of forgetting by a factor of 2 compared to ease-of-teaching. 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 $\rho$.

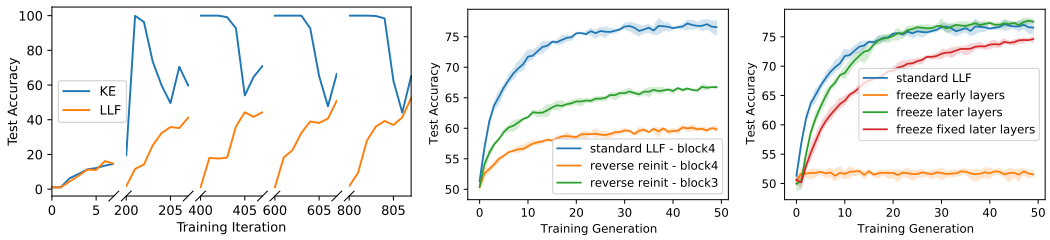
## 5 Understanding the Forget-and-Relearn dynamic

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.

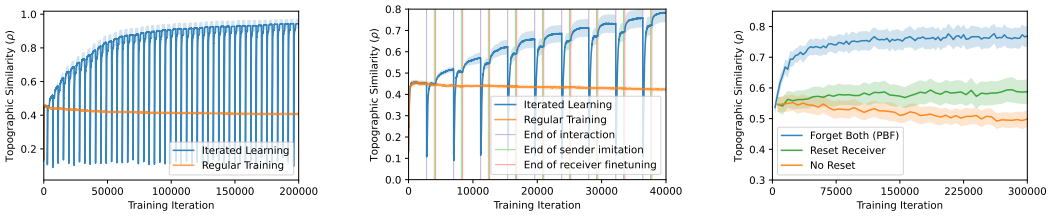
To test hypothesis 1, we freeze the early layer after the initial training generation and reinitialize the later layers for retraining in subsequent generations. If the later layers improve as a result of learning on top of well-developed early layer features, we should expect a performance improvement 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 that 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) $\rho$ increases during the retraining stage.

For iterated learning, 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 $\rho$ than the previous one, arguing that the compositional components of the language are learned first. The success of iterated learning has primarily been attributed to this increase in compositionality during the imitation phase, which follows the explanation in the cognitive science theories from which iterated learning derives (Kirby,




(a) Iterated learning.

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

(c) Ease-of-teaching.

Figure 4: Topographic similarity ($\rho$) in the Lewis game with different forms of forgetting. (a) presents the $\rho$ across all phases of iterated learning; (b) zooms into the first 40000 steps to illustrate that $\rho$ 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 $\rho$ (relearn). (c) plots $\rho$ at the end of each generation for the ease-of-teaching setting.

2001). However, when viewed as an instance of forget-and-relearn, our hypothesis predicts that the improved performance in iterated learning 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 $\rho$. By looking at $\rho$ during both the imitation and interaction phases using optimal hyperparameters under the setting in Ren et al. (2020), we see that increases in $\rho$ occur during the interaction phase, while the optimal imitation phase does not even need to result in a higher $\rho$ 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.

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# A APPENDIX

## A1 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 |

## A2 DETAILS ON TARGETED FORGETTING

### 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.

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 | $\lvert\mathbf{\Theta}_{init}\rvert$ | Once | Identity | Reinitialize |
| Same Weight Zero | $\lvert\mathbf{\Theta}_{init}\rvert$ | Once | Identity | Set to $0$ |

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 A5: 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 the validation set to tune hyperparameters and report results on the test set when available.

### A2.3 Comparison to LW

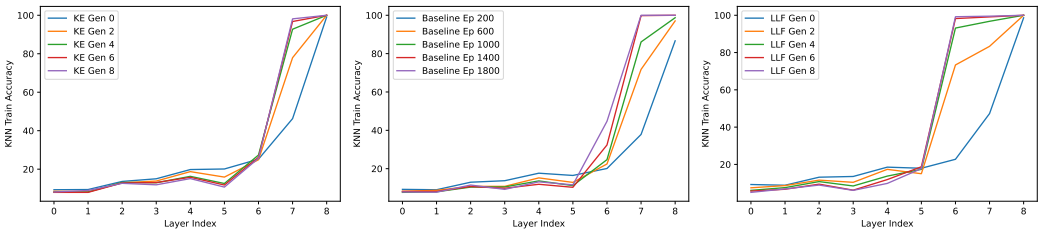
Concurrent work (Alabdulmohsin et al., 2021) studies various types of iterative reinitialization approaches and finds that reinitializing entire layers produced the best performance. They propose a layer-wise reinitialization scheme, proceeding from bottom to top and reinitializing one fewer layer each 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.

## 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 $100$,

Table A6: 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** |




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

Figure A1: 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.

and use the Adam optimizer (Kingma & Ba, 2017) with a learning rate of 0.001. The language 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.

Table A7: 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** |

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.

### 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 and each message has two tokens. Compositional languages defined by exhibiting a high topographic similarity ($\rho$) would have each input attribute-value pair mapped to a unique message token-value. Thus, we can represent the inputs and the messages both as concatenations of two one-hot vectors. In Figures A2-A6, we illustrate the mappings from these input dimensions to message dimensions. For each input dimension represented by an attribute-value pair, we collect the message probability vectors produced by the sender for each message token by varying the other input attribute across all values. Then, the mean of these message probability vectors is used as the row corresponding to the chosen input dimension. The first 8 columns represent the first message token, and the next 8 represent the second.

For iterated learning in Figure A2 and PBF in Figure A4, 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.

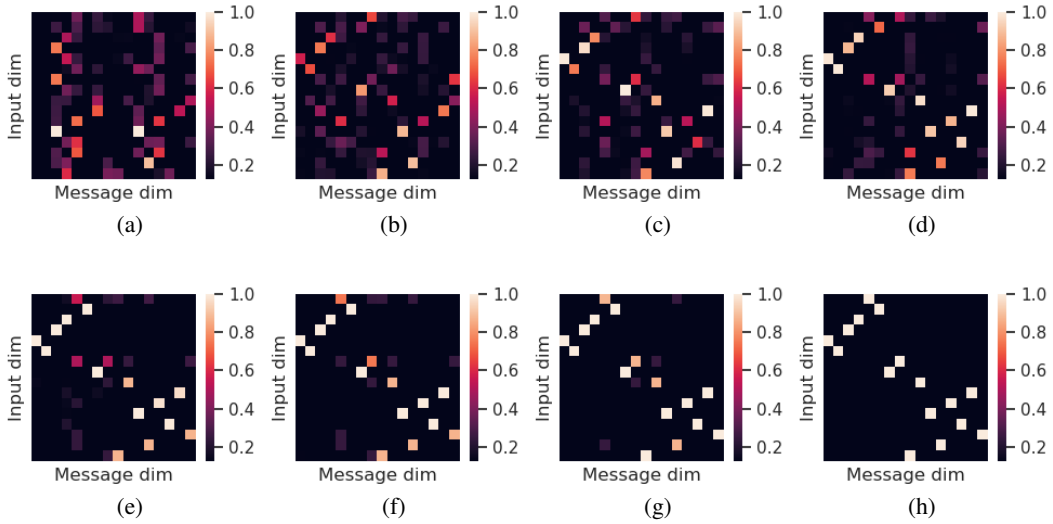



Figure A2: Mappings from input dimension to message dimension learned by the sender using **iterated learning** in the setting of Ren et al. (2020), logged after every generation for the first 32200 training iterations across all phases. A compositional language appears as a permutation matrix, where each input dimension maps to a unique message dimension.

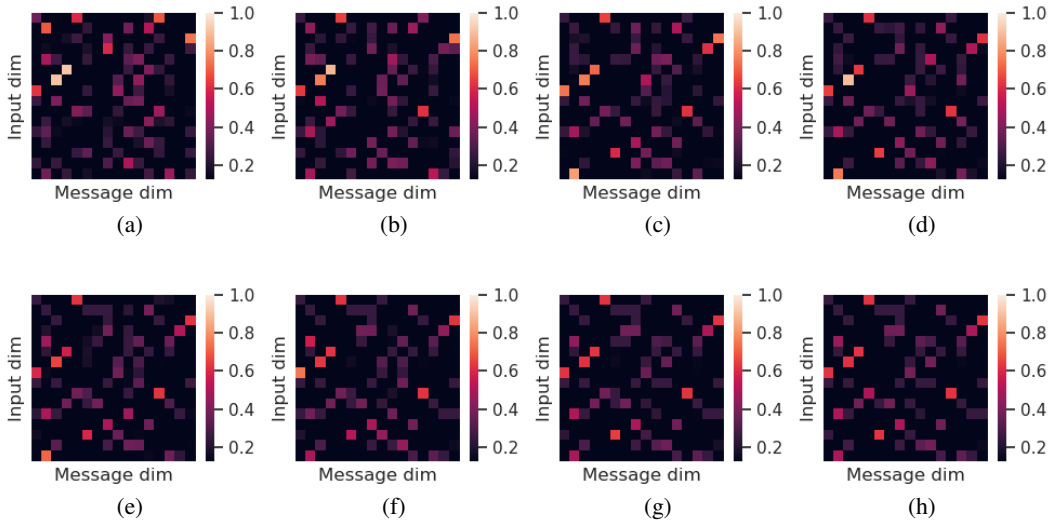



Figure A3: Mappings from input dimension to message dimension learned by the sender **without any form of forget-and-retrain** in the setting of Ren et al. (2020), logged uniformly for the first 33000 training iterations. A compositional language would have appeared as a permutation matrix, where each input dimension maps to a unique message dimension.

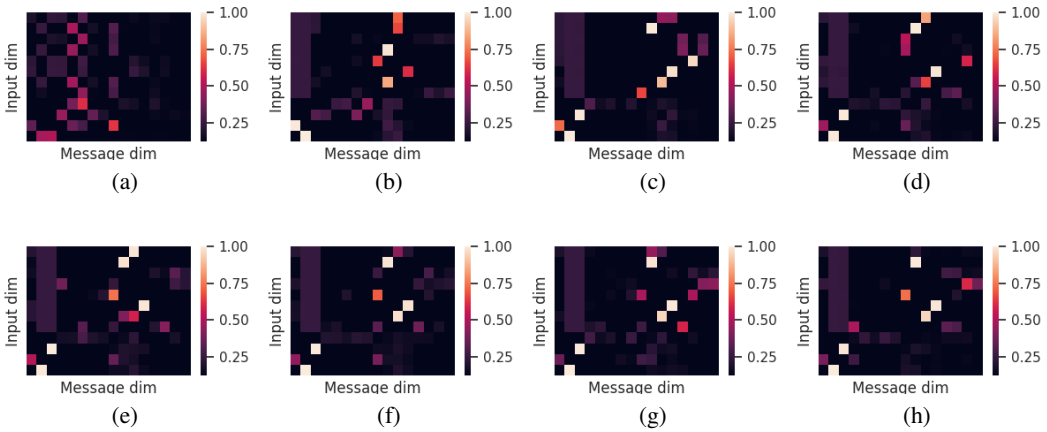



Figure A4: Mappings from input dimension to message dimension learned by the sender using **Partial Balanced Forgetting (PBF)** in the setting of Li & Bowling (2019), logged after every two generations for the first 48000 training iterations. A more compositional language has unique non-overlapping message dimension activations for different input dimensions.

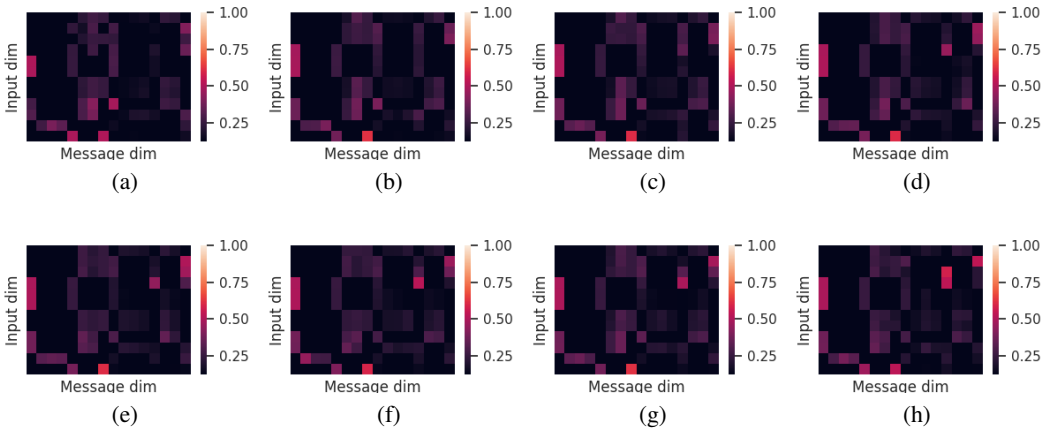



Figure A5: Mappings from input dimension to message dimension learned by the sender by **resetting the receiver periodically** following the setting of Li & Bowling (2019), logged after every generation for the first 48000 training iterations. A more compositional language has unique non-overlapping message dimension activations for different input dimensions.

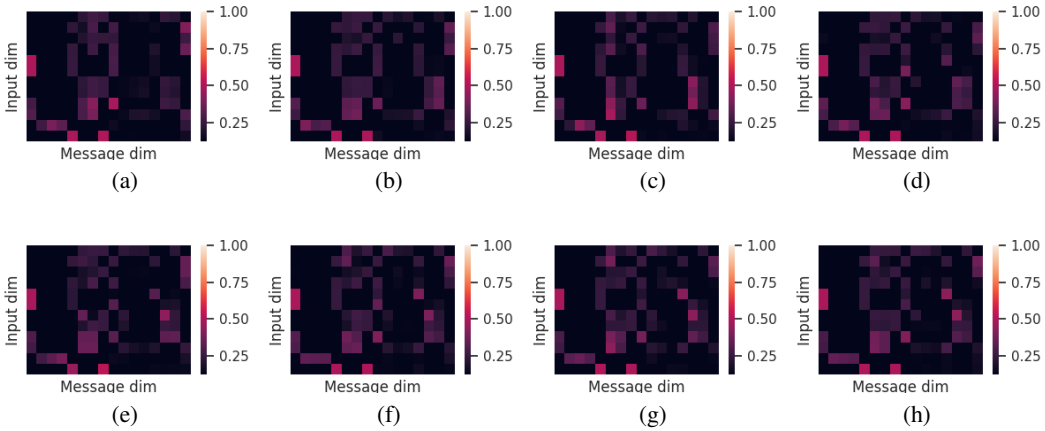



Figure A6: Mappings from input dimension to message dimension learned by the sender **without any form of forget-and-retrain** in the setting of Li & Bowling (2019), logged uniformly for the first 48000 training iterations. A more compositional language has unique non-overlapping message dimension activations for different input dimensions.