5th Symposium on Advances in Approximate Bayesian Inference, 2023 1–17

Improving Continual Learning by Accurate Gradient Reconstructions of the Past

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1. Introduction

Continual learning (Parisi et al., 2019) aims for accurate incremental training over a large number of individual tasks/examples. This can potentially reduce the frequency of retraining in deep learning, making algorithms easier to use and deploy, while also reducing their environmental impact (Diethe et al., 2019; Paleyes et al., 2020). The main challenge in continual learning is to remember past knowledge and reuse it to continue to adapt to new data. This can be difficult because the future is unknown and can interfere with past knowledge (Sutton, 1986; Mermillod et al., 2013; Kirkpatrick et al., 2017). Performance, therefore, heavily depends on the strategies used to represent and reuse past knowledge.

Two popular strategies of knowledge reuse are based on regularization and experience replay and have complementary strengths. For example, the well-known Elastic-Weight Consolidation (EWC) (Kirkpatrick et al., 2017), which regularizes the new weight-vector to keep it close to the old one, is compact and requires storing only two vectors, one containing the weights and the other their importance (often the empirical Fisher). A variety of other such regularizers have been proposed (Schwarz et al., 2018; Zenke et al., 2017b; Li and Hoiem, 2018; Nguyen et al., 2018), and are usually motivated as being approximately Bayesian over the parameters (EWC is a Laplace-style approximation). This is very different from experience replay (Robins, 1995; Shin et al., 2017), where past examples are simply added during future training. Memory cost here can be substantial, but it can boost accuracy if the memory represents the past well. Clearly, combining the two approaches can strike a good balance between performance and memory size.

At present, little has been done to find principled ways to combine the two strategies. Some works have used knowledge distillation (Rebuffi et al., 2017; Buzzega et al., 2020) or functional regularization using a Gaussian Process approximation (Titsias et al., 2020; Pan et al., 2020), where predictions evaluated at the examples in memory are regularized. Such approaches are promising, but it is not clear why the specific choices of regularizers and memory work well and whether there are better choices that lead to further improvements.

In this paper, we provide a principled approach to combine and improve the two strategies. Our approach is based on a recently proposed principle of adaptation (Khan and Swaroop, 2021), where a prior called the Knowledge-adaptation prior (K-prior) is used to reconstruct the gradients of the past training objective. In the continual learning setting, this requires an accurate reconstruction of the gradients over all the past tasks, and can be used as a guideline to design better priors. Khan and Swaroop (2021) considered only one-task adaptation, which does not consider the errors accumulated over multiple tasks in problems like continual learning. They also used a simple quadratic regularizer, and did not employ experience replay. Our goal here is to extend their method to multiple tasks and use it to combine different regularization and replay methods.

Using the principle of gradient reconstruction of the past, we design a prior that combines a Bayesian weight-regularizer, a functional regularizer, and experience replay (Fig. 2). Each piece contributes to the reduction in the gradient-reconstruction error. This leads to consistent improvements on standard benchmarks for multi-task image classification in task-incremental continual learning, such as Split CIFAR, Split TinyImageNet, and ImageNet-1000, across various memory budgets from small to large sizes. This approach is principled and can yield provably better strategies than the current heuristics used in the literature.

2. Continual Learning Methods

We focus on a continual learning (CL) problem to incrementally learn from a sequence of data sets $\mathcal{D}_1, \ldots, \mathcal{D}_T$, corresponding to a total of T tasks. This is different from the commonly used batch-training in deep learning, where data from all the tasks is assumed to be available at all times during training. CL is challenging as the model needs to repeatedly adapt to new tasks, while not forgetting previous-gathered knowledge. Our goal is to get the performance as close as possible to the model that is trained on data from all tasks.

Formally, consider a supervised learning problem with $\mathcal{D}_t$ containing N input-output pairs $(\boldsymbol{x}_i, y_i)$, with $\boldsymbol{x}_i \in \mathbb{R}^D$ and $y_i \in \mathcal{Y}$, and we wish to train a model with output $f_{\boldsymbol{w}}(\boldsymbol{x}_i)$ (also denoted as $f^i_{\boldsymbol{w}}$), and a P-length parameter $\boldsymbol{w}$ in a space $\mathcal{W} \subseteq \mathbb{R}^P$. Then, at any given task t, the best possible model parameters $\boldsymbol{w}^\star_t$ can be obtained by training on all the data examples $\mathcal{D}_{1:t} = \bigcup_{i=1}^t \mathcal{D}_i$, for example, by solving the optimization problem shown below,

$$\boldsymbol{w}^\star_t = \arg\min_{\boldsymbol{w} \in \mathcal{W}} \ell^{\text{batch}}_t(\boldsymbol{w}), \quad \text{where} \quad \ell^{\text{batch}}_t(\boldsymbol{w}) = \sum_{i \in \mathcal{D}_{1:t}} \ell\big(y_i, h(f^i_{\boldsymbol{w}})\big) + \mathcal{R}(\boldsymbol{w}). \tag{1}$$

We assume the loss $\ell(y_i, h(f_i))$ is defined through the log-likelihood of an exponential family distribution (e.g., cross-entropy), with $h(f)$ being a transformation of the model outputs (e.g., softmax) defined using the link-function of the distribution. We denote a regularizer by $\mathcal{R}(\boldsymbol{w})$, and in what follows, we will use an L_2 regularizer $\mathcal{R}(\boldsymbol{w}) = \frac{1}{2}\delta \|\boldsymbol{w}\|^2$, with $\delta > 0$.

The main challenge in CL is to remember the useful past knowledge extracted from previous tasks $\mathcal{D}_{1:t-1}$, and reuse it during training over the new task $\mathcal{D}_t$ to get as close as possible to $\boldsymbol{w}_t^\star$. We would like a compact summary of the past knowledge, because we are not allowed to store all past data. We will now describe two strategies used in the literature, based on regularization and experience replay, and discuss the challenges in combining them.

Regularization-based approaches try to keep the new weight-vector close to the old one, aiming to avoid forgetting and facilitate knowledge reuse. The most common is a weight-regularization technique known as Elastic-Weight Consolidation (EWC) (Kirkpatrick et al., 2017), which, at a task t, minimizes the following objective using the previous weight $\boldsymbol{w}_{t-1}$,

$$\ell_t^{\text{weight}}(\boldsymbol{w}) = \sum_{i \in \mathcal{D}_t} \ell\big(y_i, h(f_{\boldsymbol{w}}^i)\big) + \frac{\lambda}{2}(\boldsymbol{w} - \boldsymbol{w}_{t-1})^\top \mathbf{F}_{t-1}(\boldsymbol{w} - \boldsymbol{w}_{t-1}), \tag{2}$$

where the second term is a quadratic regularizer with a weight-importance matrix $\mathbf{F}_{t-1}$, and $\lambda \geq 0$ is a trade-off hyperparameter. The simplest choice of $\mathbf{F}_{t-1}$ is to use the diagonal of a generalized Gauss-Newton (GGN) matrix (Martens, 2014, definition in Appendix B), motivated as it corresponds to a Bayesian update with Laplace approximations. This method uses a compact representation of the past knowledge as we need to only store $\boldsymbol{w}_{t-1}$ and the diagonal matrix $\mathbf{F}_{t-1}$, requiring $O(P)$ memory. Other choices are possible for the importance matrix (Zenke et al., 2017a; Aljundi et al., 2018; Benzing, 2022). This method is also simple to implement within deep-learning codebases, requiring little overhead.

An alternative to regularization-based methods are experience replay techniques (Robins, 1995; Shin et al., 2017). These store a subset of past data in a memory $\mathcal{M}_t$ and add it to the new data during training, and can be accurate when the memory represents the data well, but often require a large memory that grows with the number of tasks:

$$\ell_t^{\text{er}}(\boldsymbol{w}) = \sum_{i \in \mathcal{D}_t \cup \mathcal{M}_{t-1}} \ell\big(y_i, h(f_{\boldsymbol{w}}^i)\big)\,.$$

A popular approach to combine these two previous approaches is to use functional regularization (Titsias et al., 2020; Pan et al., 2020) where, instead of regularizing the weights, we regularize the function outputs at a few past input locations stored in a memory:

$$\ell_t^{\text{func}}(\boldsymbol{w}) = \sum_{i \in \mathcal{D}_t} \ell\big(y_i, h(f_{\boldsymbol{w}}^i)\big) + \frac{\lambda}{2} \sum_{j \in \mathcal{M}_{t-1}} \ell\left(h(f_{\boldsymbol{w}_{t-1}}^j),\, h(f_{\boldsymbol{w}}^j)\right). \tag{3}$$

Some methods implement this via knowledge-distillation (Rebuffi et al., 2017; Buzzega et al., 2020), and some also simply use the squared loss instead of using the original loss (Benjamin et al., 2019). An advantage of functional regularization is that it does not require the labels associated with the inputs in $\mathcal{M}_t$, which enables using an arbitrary input $\boldsymbol{x}$ not restricted to be from $\mathcal{D}_{1:t}$. For example, we can use a deep generative model to generate pseudo-inputs (Shin et al., 2017), or learn them as in sparse Gaussian processes (Titsias et al., 2020).

Each method has its own complementary strengths: Weight-regularization is compact, experience replay can be accurate, and functional regularization can use arbitrary memory inputs. Combining these approaches can strike a good balance between performance and memory size, but at present, little has been done to find principled ways to combine them.

One could simply add them together, but there are many choices to make. For example, how should we choose the importance matrix, the memory set, and the specific forms of the regularizers? Our goal is to provide a principled approach to answer such questions.

3. Principle of Adaptation: Gradient Reconstruction of the Past

We will use the recently proposed principle of adaptation by Khan and Swaroop (2021) to combine and improve the CL strategies discussed in Section 2. The principle suggests to reconstruct the gradient of the past objective by using a combination of weight and function-space regularizers. Specifically, at task t, we consider minimizing (for some $\tau > 0$)

$$\ell_t^{\text{K-prior}}(\boldsymbol{w}) = \sum_{i \in \mathcal{D}_t} \ell\big(y_i, h(f^i_{\boldsymbol{w}})\big) + \tau\, \mathcal{K}(\boldsymbol{w}; \boldsymbol{w}_{t-1}, \mathcal{M}_{t-1}), \tag{4}$$

where $\mathcal{K}(\boldsymbol{w}; \boldsymbol{w}_t, \mathcal{M}_t)$ is a regularizer that combines a weight-space regularizer using $\boldsymbol{w}_t$ and a function-space regularizer over the memory $\mathcal{M}_t$. The regularizer is called the Knowledge-adaptation prior (K-prior), and is designed with the goal to minimize the gradient reconstruction error of the past training objective. We will use $\tau = 1$ unless noted otherwise.

Specifically, at task t, the past training objective is $\ell_{t-1}^{\text{batch}}(\boldsymbol{w})$, and we want to design the prior to minimize the magnitude of the gradient error for all $\boldsymbol{w}$:

$$\boldsymbol{e}_t(\boldsymbol{w}) := \nabla \ell_{t-1}^{\text{batch}}(\boldsymbol{w}) \quad \nabla \mathcal{K}(\boldsymbol{w}; \boldsymbol{w}_{t-1}, \mathcal{M}_{t-1}).$$

The loss $\ell_{t-1}^{\text{batch}}$ depends on all the past data $\mathcal{D}_{1:t-1}$, and our goal is to reconstruct its gradient by using the weight vector $\boldsymbol{w}_{t-1}$ and a memory $\mathcal{M}_{t-1}$. Khan and Swaroop (2021) showed that many existing adaptive strategies in machine learning for one-step adaptation tasks can be recovered from this principle. For example, for generalized-linear models $f^i_{\boldsymbol{w}} = \boldsymbol{x}_i^\top \boldsymbol{w}$, the error $\boldsymbol{e}_t(\boldsymbol{w})$ is zero when we use the following K-prior with $\mathcal{M}_{t-1} = \mathcal{D}_{1:t-1}$:

$$\mathcal{K}(\boldsymbol{w}; \boldsymbol{w}_{t-1}, \mathcal{M}_{t-1}) = \sum_{i \in \mathcal{M}_{t-1}} \ell\Big(h(f^i_{\boldsymbol{w}_{t-1}}), h(f^i_{\boldsymbol{w}})\Big) + \frac{\delta}{2}(\boldsymbol{w} \quad \boldsymbol{w}_{t-1})^\top (\boldsymbol{w} \quad \boldsymbol{w}_{t-1}), \tag{5}$$

where $\delta \quad 0$ is the L_2 regularization constant. This is surprising because the K-prior does not use the labels, just like the functional regularization discussed earlier, yet the gradient can be reconstructed by using the predictions at the inputs locations $\boldsymbol{x}_i \in \mathcal{D}_{1:t-1}$. Many other similar results are shown by Khan and Swaroop (2021) for other models, such as support vector machines, Gaussian processes, variational inference, knowledge distillation, functional-regularization, and the memory-based methods used in continual learning.

While promising, there are still multiple issues with the work of Khan and Swaroop (2021), which we will fix in this paper. First, they did not design priors for a multi-task setup such as continual learning. Second, the error incurred by their K-prior, of form Eq. (5), is non-zero for neural networks: see Khan and Swaroop (2021, Sec. 4.2). For the continual learning problem, this can be disastrous because errors can accumulate quickly over tasks, deteriorating performance. Third, the weight-regularizer in Eq. (5) ignores the weight importance, which is commonly used in other works (Kirkpatrick et al., 2017; Schwarz et al., 2018; Ritter et al., 2018) and can improve performance.

In this paper, we will fix these issues, combining and improving regularization and memory-based methods. We will start with functional-regularization, and then add a weight regularizer and experience replay to decrease its error. This will give us a prior that provably gives better error than each individual method on its own.

4. A New Improved K-prior

Using the principle described in the previous section, we will now design a prior that combines a weight regularizer, a functional regularizer, and experience replay (Fig. 2).

The error in the K-prior Eq. (5) when using a limited memory. We start by analyzing the error in the K-prior of Eq. (5) when it is defined with a limited memory M_{t-1}, instead of the full data $D_{1:t-1}$. As shown in Appendix D, it is given as,

$$\boldsymbol{e}_t(\boldsymbol{w}) = \underbrace{\sum_{i \in D_{1:t-1} \cap M_{t-1}} r f^i_{\boldsymbol{w}} \left[h(f^i_{\boldsymbol{w}}) \quad h(f^i_{\boldsymbol{w}_{t-1}}) \right]}_{:= \boldsymbol{e}^{\text{mem}}(\boldsymbol{w}; \boldsymbol{w}_{t-1}, D_{1:t-1} \cap M_{t-1})} + \underbrace{\sum_{i \in D_{1:t-1}} r f^i_{\boldsymbol{w}} r^i_{\boldsymbol{w}_{t-1}} + \delta \boldsymbol{w}_{t-1}}_{:= \boldsymbol{e}^{\text{NN}}(\boldsymbol{w}; \boldsymbol{w}_{t-1}, D_{1:t-1})}, \tag{6}$$

where $r^i_{\boldsymbol{w}_t} = h(f^i_{\boldsymbol{w}_t}) \quad y_i$ is the residual left after prediction. The first error term $\boldsymbol{e}^{\text{mem}}$ arises due to the use of limited memory M_{t-1}, and can be reduced to zero by increasing the memory size to include all past input examples. In contrast, the second error term $\boldsymbol{e}^{\text{NN}}$ arises due to the use of neural networks, and reduces only when the network gets better in predicting the past data $D_{1:t-1}$, that is, when the residuals go to zero. In Appendix C, we show that that $\boldsymbol{e}^{\text{mem}}$ can be reduced by adding an EWC-style weight regularizer, while $\boldsymbol{e}^{\text{NN}}$ can be reduced by adding an experience replay term with a specific memory.

K-prior with EWC-style regularizer and Experience Replay. Therefore, we can write the new K-prior as (see Appendix C for the detailed derivation),

$$K^{\text{new}}(\boldsymbol{w}; \boldsymbol{w}_{t-1}, M_{t-1}) = \underbrace{\sum_{i \in M_{1,t-1}} \ell\Big(h(f^i_{\boldsymbol{w}_{t-1}}), h(f^i_{\boldsymbol{w}})\Big)}_{\text{Functional-regularization}} + \underbrace{\sum_{i \in M_{2,t-1}} \ell\big(y_i, h(f^i_{\boldsymbol{w}})\big)}_{\text{Experience replay}}$$
$$+ \underbrace{\tfrac{1}{2}(\boldsymbol{w} \quad \boldsymbol{w}_{t-1})^\top \mathbf{F}_{t-1} (\boldsymbol{w} \quad \boldsymbol{w}_{t-1}) + \tfrac{1}{2}\delta \boldsymbol{w}^\top \boldsymbol{w}_{t-1}}_{\text{Weight-regularization}}, \tag{7}$$

where $M_{1,t-1}$ and $M_{2,t-1}$ are two disjoint subsets of the memory (i.e., $M_{1,t-1} \cup M_{2,t-1} = M_{t-1}$, $M_{1,t-1} \setminus M_{2,t-1} = \emptyset$), and where we define $\mathbf{F}_{t-1} = \mathbf{G}(D_{1:t-1} \cap M_{t-1}) + \delta \mathbf{I}$. The new prior combines a weight regularizer, a functional regularizer, and experience replay. The functional regularizer is based on knowledge distillation, and combined with an EWC-style quadratic regularizer which uses an importance vector obtained over all the past data but excluding the memory M_{t-1}. Using this combination, the new prior gives provably lower gradient reconstruction error than each method alone (see Appendix C for details).

In our experiments, we first randomly (uniformly) sample the memory set M_{t-1} from all data $D_{1:t-1}$, and then randomly split it into the two memory subsets $M_{1,t-1}$ and $M_{2,t-1}$; for simplicity, we use equally sized subsets, i.e., $|M_{1,t-1}| = |M_{2,t-1}|$. We found this simple selection strategy to work surprisingly well, and leave the study of more sophisticated approaches (as well as of settings where $|M_{1,t-1}| \neq |M_{2,t-1}|$) for future work.

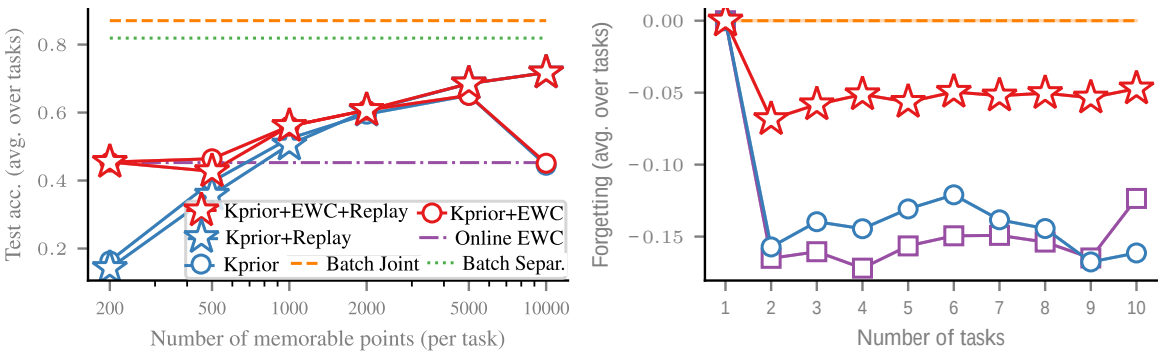

Figure 1: Kprior+EWC+Replay performs favorably across memory sizes (left; x-axis log-scaled), and suffers less from forgetting (relative to Batch Joint) with an increasing number of tasks, here exemplary shown at the largest memory size of 10K (right).

5. Empirical evaluation

We present results on the large-scale ImageNet-1000 CL benchmark (Rebuffi et al., 2017) corroborating the practical efficacy of our proposed Kprior+EWC+Replay method. For further details on the experimental setup as well as additional results on the Split-CIFAR and Split-TinyImageNet benchmarks (with similar conclusions), see Appendix E. ImageNet-1000 randomly (uniformly) splits the full ImageNet dataset (Deng et al., 2009) of 1.2M data points into a sequence of 10 tasks with 100 classes and 120K data points each. Following Rebuffi et al. (2017), we use a ResNet-18 with 11M model parameters. For training on each task, we use the ImageNet reference training pipeline (with 40 epoch configuration) of the FFCV library (Leclerc et al., 2022). Fig. 1 shows our results. We consider memory sizes between 200 and 10K per task, where the latter amounts to just under 10% of the data. `Kprior` underperforms for small memory sizes, and while it improves with increasing memory, it peaks at a 5K memory and then even starts declining. We hypothesize that this is due to accumulation of the NN error, which might become more severe with a larger memory as more data points can contribute to the error. This is evidenced by the fact that correcting for the NN error (`Kprior+Replay`) substantially boosts performance at a 10K memory (but it remains poor at small memories). In contrast, `Kprior+EWC` improves accuracy only for small memories. Finally, `Kprior+EWC+Replay` combines the benefit of both error correction terms to perform well across all memory sizes, achieving $>80\%$ of the batch performance with a memory of $<10\%$ of the past data. It also forgets less along the task sequence, demonstrating that it better mitigates error accumulation.

6. Conclusion

We proposed to address the CL problem in a theoretically-grounded way by explicitly approximating the optimal model obtained via batch-training on all tasks jointly. To this end, we developed Kprior+EWC+Replay, which efficiently re-uses prior knowledge by combining principles from function-regularization, weight-regularization, and experience replay. Empirically, we demonstrated the effectiveness and scalability of our method.

Acknowledgements

We would like to thank Runa Eschenhagen for many helpful discussions throughout the project. ED acknowledges funding from the EPSRC and Qualcomm. MEK and RY are supported by the Bayes duality project, JST CREST Grant Number JPMJCR2112.

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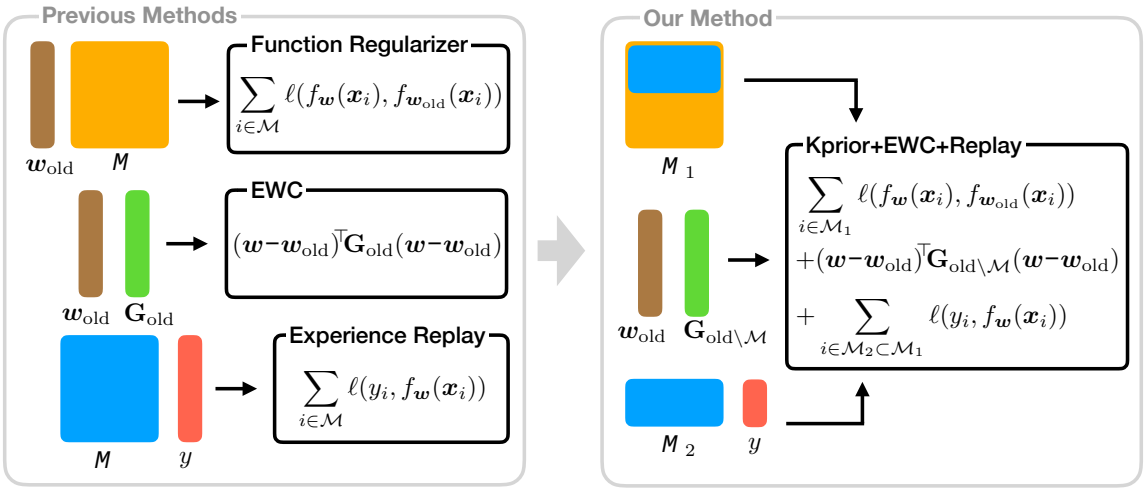

Figure 2: Using the principle of gradient reconstructions, we design a new prior (right) to combine different types of regularization and memory-based methods. EWC uses a quadratic regularizer based on the old weight-vector and its importance, while experience replay uses a memory of past examples along with their labels. Function regularization often does not require the labels, but also lacks a weight regularizer. Our method combines these different types of methods. The notable differences are that our method's importance vector excludes the examples in the memory set, and that experience replay is applied only to the second memory set. The rest of the examples in the memory set do not require labels, and can be compressed to only keep a small set of representative inputs that may not be part of the old training sets.

Appendix A. Illustrative Diagram

Fig. 2 illustrates our proposed approach.

Appendix B. Definition of the Generalized Gauss-Newton matrix

The simplest choice of the weight-importance matrix $\mathbf{F}_{t\ 1}$ in EWC is to use the diagonal of a generalized Gauss-Newton (GGN) matrix (Martens, 2014), where the GGN is defined as,

$$\mathbf{G}(D_{1:t}) := \sum_{i2D_{1:t}} \left[r\, f^i_{\boldsymbol{w}_t} \right] h^{\emptyset}(f^i_{\boldsymbol{w}_t}) \left[r\, f^i_{\boldsymbol{w}_t} \right]^{>}, \tag{8}$$

where $r\, f^i_{\boldsymbol{w}_t}$ denotes the derivative of $f_{\boldsymbol{w}}(\boldsymbol{x}_i)$ with respect to $\boldsymbol{w}$ at $\boldsymbol{w}_t$ (the Jacobian), and $h^{\emptyset}(f^i)$ denotes the derivative of $h(f)$ with respect to f and evaluated at a function value f^i. Often, the regularizer δ is added to the GGN matrix to reduce ill-conditioning. Computation of $\mathbf{F}_{t\ 1}$ can be done in an online fashion as the training proceeds over tasks (Schwarz et al., 2018).

Appendix C. Derivation of our new Improved K-prior

We here derive our improved K-prior proposed in Section 4. To this end, we will now show that the error $\boldsymbol{e}^{\text{mem}}$ in Eq. (6) can be reduced by adding an EWC-style weight regularizer, while the error $\boldsymbol{e}^{\text{NN}}$ in Eq. (6) can be reduced by adding an experience replay term with a specific memory.

C.1. Reducing $\mathbf{e}^{\text{mem}}$ using an EWC-style regularizer

The error $\boldsymbol{e}^{\text{mem}}$ can be reduced by using a first-order Taylor approximation of $h(f^i_w)$ at $\boldsymbol{w}_{t\ 1}$,

$$h(f^i_{\boldsymbol{w}}) \quad h(f^i_{\boldsymbol{w}_t\ 1}) + h^{\emptyset}(f^i_{\boldsymbol{w}_t\ 1})(\ r\ f^i_{\boldsymbol{w}_t\ 1})^{>}(\boldsymbol{w} \quad \boldsymbol{w}_{t\ 1}). \tag{9}$$

Plugging this in the definition of the error, we get

$$\boldsymbol{e}^{\text{mem}}_t \quad \underbrace{\left[\sum_{i2D_{1:t\ 1}n M_{t\ 1}} \left[\ r\ f^i_{\boldsymbol{w}_t\ 1}\right] h^{\emptyset}(f^i_{\boldsymbol{w}_t\ 1}) \left[\ r\ f^i_{\boldsymbol{w}_t\ 1}\right]^{>}\right]}_{=\mathbf{G}(D_{1:t\ 1}n M_{t\ 1})} (\boldsymbol{w} \quad \boldsymbol{w}_{t\ 1})$$

where we use the definition of the GGN matrix given in Eq. (8). The right hand side is equal to the gradient of the an EWC-style regularizer,

$$\boldsymbol{c}^{\text{mem}}_t = (\boldsymbol{w} \quad \boldsymbol{w}_{t\ 1})^{>}\mathbf{G}(D_{1:t\ 1}n M_{t\ 1})(\boldsymbol{w} \quad \boldsymbol{w}_{t\ 1}), \tag{10}$$

which uses the GGN over the past data but excludes the memory $M_{t\ 1}$ from it. We can now define a new K-prior by adding the correction term as follows $K_t + \boldsymbol{c}^{\text{mem}}_t$, which gives,

$$K^{\text{mem}}_{\text{cor}}(\boldsymbol{w}; \boldsymbol{w}_{t\ 1}, M_{t\ 1}) := \sum_{i2\, M_{t\ 1}} \ell\Big(h(f^i_{\boldsymbol{w}_t\ 1}), h(f^i_{\boldsymbol{w}})\Big) + \tfrac{1}{2}(\boldsymbol{w} \quad \boldsymbol{w}_{t\ 1})^{>}\mathbf{F}_{t\ 1}(\boldsymbol{w} \quad \boldsymbol{w}_{t\ 1}). \tag{11}$$

where we define $\mathbf{F}_{t\ 1} = \mathbf{G}(D_{1:t\ 1}n M_{t\ 1}) + \delta\mathbf{I}$. This K-prior provably reduces the error introduced in the K-prior of Eq. (5) due to a limited memory. Similarly to Online EWC, we can use a diagonal approximation to the GGN, and update it online.

The new K-prior not only reduces the gradient error, but also is more general because other regularizers are obtained as special cases by changing the memory. For an empty memory $M_{t\ 1} = ;$, it reduces to the EWC regularizer of Eq. (2) because then the first term in Eq. (11) disappears and the importance $\mathbf{F}_t$ is the GGN defined over all the past data, plus $\delta\mathbf{I}$. On the other hand, when the memory includes all past data, it reduces to the original K-prior in Eq. (5). When using limited memory, the new K-prior combines the functional and weight regularizer in a way to reduce the error in both EWC and the original K-prior.

C.2. Reducing e^{NN} using Experience Replay

The e^{NN} term depends on the mistakes made on the past data, and can be corrected by including an additional memory $M_{2,t\ \ 1}$ of the past data where mistakes are significant. We first note that the error is equivalent to the gradient of the following,

$$c_t^{\text{NN}} := \sum_{i2 M_{2,t\ \ 1}} f_{w}^{i} r_{w_{t\ \ 1}}^{i} + \tfrac{1}{2}\delta w^{>} w_{t\ \ 1}, \tag{12}$$

when $M_{2,t\ \ 1}$ is set to all the past data. Therefore, by adding $K_{\text{cor}}^{\text{NN}} = K_t + c_t^{\text{NN}}$, we reduce the error simply to $\sum_{i2 D_{1:t\ \ 1} n M_2} \left[r\, f_{w}^{i} r_{w_{t\ \ 1}}^{i} \right]$.

C.3. K-prior with EWC-style regularizer and Experience Replay

Our new improved K-prior is obtained by simply correcting the K-prior from Eq. (5) by adding the correction terms, that is, $K_t^{\text{new}} = K_t + c_t^{\text{mem}} + c_t^{\text{NN}}$. We make a specific choice of the memory: we choose $M_{2,t\ \ 1}$ to be a subset of M_1. This, as we show now, simplifies the computation and brings experience replay into our new K-prior.

Consider the following two terms taken from $K_{\text{cor}}^{\text{mem}}$ from Eq. (11) and $K_{\text{cor}}^{\text{NN}}$ from Eq. (12).

$$\sum_{i2 M_{t\ \ 1}} \ell\left(h(f_{w_{t\ \ 1}}^{i}), h(f_{w}^{i})\right) + \sum_{i2 M_{2,t\ \ 1}} f_{w}^{i} r_{w_{t\ \ 1}}^{i}$$

The gradient of these two can be simplified, when the second memory is a subset of the first one,

$$\begin{aligned}
&\sum_{i2 M_{t\ \ 1}} r\, f_{w}^{i} \left[h(f_{w}^{i}) \quad h(f_{w_{t\ \ 1}}^{i}) \right] + \sum_{i2 M_{2,t\ \ 1}} r\, f_{w}^{i} r_{w_{t\ \ 1}}^{i} \\
&= \sum_{i2 M_{t\ \ 1} n M_{2,t\ \ 1}} r\, f_{w}^{i} \left[h(f_{w}^{i}) \quad h(f_{w_{t\ \ 1}}^{i}) \right] + \sum_{i2 M_{2,t\ \ 1}} r\, f_{w}^{i} \left[h(f_{w}^{i}) \quad h(f_{w_{t\ \ 1}}^{i}) \right] + r\, f_{w}^{i} r_{w_{t\ \ 1}}^{i} \\
&= \sum_{i2 M_{t\ \ 1} n M_{2,t\ \ 1}} r\, f_{w}^{i} \left[h(f_{w}^{i}) \quad h(f_{w_{t\ \ 1}}^{i}) \right] + \sum_{i2 M_{2,t\ \ 1}} r\, f_{w}^{i} \left[h(f_{w}^{i}) \quad y_i) \right]
\end{aligned}$$

where in the last line we used the definition of the residual to simplify. This gradient is equal to the gradient of a sum of a functional-regularizer term and an experience replay term,

$$\sum_{i2 M_{t\ \ 1} n M_{2,t\ \ 1}} \ell\left(h(f_{w_{t\ \ 1}}^{i}), h(f_{w}^{i})\right) + \sum_{i2 M_{2,t\ \ 1}} \ell\big(y_i, h(f_{w}^{i})\big) \tag{13}$$

Therefore, we can rewrite the new K-prior as the combination in Eq. (7) in Section 4.

Appendix D. Derivation of error for K-priors with limited memory Eq. (6)

Recall that $f_{w}^{i} = f_{w}(x_i)$ is a shorthand for the model outputs. For ease-of-notation, we will also use the shorthand $h_{w}^{i} := h(f_{w}^{i}) = h(f_{w}(x_i))$ for the model predictions. Consider the

following expression for the gradient of the (exponential-family) loss (Khan and Swaroop, 2021),

$$\nabla \ell(y_i, h(f_{\boldsymbol{w}}^i)) = \nabla f_{\boldsymbol{w}}^i \left[\nabla h(f_{\boldsymbol{w}}^i) \quad y_i\right]. \tag{14}$$

We then have,

$$\begin{aligned}
&\nabla \ell_t^{\text{batch}}(\boldsymbol{w}) \quad \nabla \ell_t^{\text{K-prior}}(\boldsymbol{w}) \\
&= \nabla \left(\ell_t^{\text{batch}}(\boldsymbol{w}) \quad \ell_t^{\text{K-prior}}(\boldsymbol{w})\right) \\
&\overset{(1),(4)}{=} \nabla \left(\sum_{i \in D_t} \ell\left(y_i, h_{\boldsymbol{w}}^i\right) + \ell_{t-1}^{\text{batch}}(\boldsymbol{w}) \quad \sum_{i \in D_t} \ell\left(y_i, h_{\boldsymbol{w}}^i\right) \quad K(\boldsymbol{w}; \boldsymbol{w}_{t-1}, M)\right) \\
&= \nabla \left(\ell_{t-1}^{\text{batch}}(\boldsymbol{w}) \quad K(\boldsymbol{w}; \boldsymbol{w}_{t-1}, M)\right) \\
&\overset{(1),(5)}{=} \nabla \left(\sum_{i \in D_{1:t-1}} \ell\left(y_i, h_{\boldsymbol{w}}^i\right) \quad \sum_{i \in M} \ell\left(h_{\boldsymbol{w}_{t-1}}^i, h_{\boldsymbol{w}}^i\right) + \tfrac{1}{2}\delta k \boldsymbol{w}_{t-1} k^2\right) \\
&= \sum_{i \in D_{1:t-1}} \nabla \ell\left(y_i, h_{\boldsymbol{w}}^i\right) \quad \sum_{i \in M} \nabla \ell\left(h_{\boldsymbol{w}_{t-1}}^i, h_{\boldsymbol{w}}^i\right) + \delta \boldsymbol{w}_{t-1} \\
&\overset{(14)}{=} \sum_{i \in D_{1:t-1}} \nabla f_{\boldsymbol{w}}^i \left[h_{\boldsymbol{w}}^i \quad y_i\right] \quad \sum_{i \in M} \nabla f_{\boldsymbol{w}}^i \left[h_{\boldsymbol{w}}^i \quad h_{\boldsymbol{w}_{t-1}}^i\right] + \delta \boldsymbol{w}_{t-1} \\
&= \sum_{i \in D_{1:t-1}} \nabla f_{\boldsymbol{w}}^i \left[h_{\boldsymbol{w}}^i \quad y_i + h_{\boldsymbol{w}_{t-1}}^i \quad h_{\boldsymbol{w}}^i + h_{\boldsymbol{w}}^i \quad h_{\boldsymbol{w}_{t-1}}^i\right] \quad \sum_{i \in M} \nabla f_{\boldsymbol{w}}^i \left[h_{\boldsymbol{w}}^i \quad h_{\boldsymbol{w}_{t-1}}^i\right] + \delta \boldsymbol{w}_{t-1} \\
&= \sum_{i \in D_{1:t-1}} \nabla f_{\boldsymbol{w}}^i \left[h_{\boldsymbol{w}_{t-1}}^i \quad y_i\right] + \sum_{i \in D_{1:t-1}} \nabla f_{\boldsymbol{w}}^i \left[h_{\boldsymbol{w}}^i \quad h_{\boldsymbol{w}_{t-1}}^i\right] \quad \sum_{i \in M} \nabla f_{\boldsymbol{w}}^i \left[h_{\boldsymbol{w}}^i \quad h_{\boldsymbol{w}_{t-1}}^i\right] + \delta \boldsymbol{w}_{t-1} \\
&= \sum_{i \in D_{1:t-1} \setminus M} \nabla f_{\boldsymbol{w}}^i \left[h_{\boldsymbol{w}}^i \quad h_{\boldsymbol{w}_{t-1}}^i\right] + \sum_{i \in D_{1:t-1}} \nabla f_{\boldsymbol{w}}^i \left[h_{\boldsymbol{w}_{t-1}}^i \quad y_i\right] + \delta \boldsymbol{w}_{t-1} \\
&= \sum_{i \in D_{1:t-1} \setminus M} \nabla f_{\boldsymbol{w}}^i \left[h_{\boldsymbol{w}}^i \quad h_{\boldsymbol{w}_{t-1}}^i\right] + \sum_{i \in D_{1:t-1}} \nabla f_{\boldsymbol{w}}^i r_{\boldsymbol{w}_{t-1}}^i + \delta \boldsymbol{w}_{t-1}
\end{aligned}$$

where $r_{\boldsymbol{w}_{t-1}}^i = h_{\boldsymbol{w}_{t-1}}^i \quad y_i$ is the residual of the i'th input using the past model parameters $\boldsymbol{w}_{t-1}$.

Appendix E. Experimental setup and additional results

We first describe the general experimental setup used throughout our evaluation. We then present empirical results corroborating the practical efficacy of our proposed Kprior+EWC+Replay method. We focus on multi-class classification in the task-incremental learning setting. In particular, we evaluate on three continual learning benchmarks with increasing size and thus difficulty: 1) Split-CIFAR (medium-scale), 2) Split-TinyImageNet (medium-to-large-scale), and 3) ImageNet-1000 (large-scale; results are presented in Section 5). See Appendix F for more details on the experiments (e.g. hyperparameters used).

E.1. Experimental setup

CL setup. We mostly follow previous works on CL. We consider the common multi-head task-incremental (Van de Ven and Tolias, 2019) setting with known task identities: each method is trained sequentially on all tasks with a separate classification head per task, and is told which task an input belongs to both at train and test time. We report test accuracy of the final model trained on the entire task sequence (averaged over the test sets of all observed tasks). We also compute average forgetting (aka backward-transfer) as defined in Lopez-Paz and Ranzato (2017), which captures the (average) difference in accuracy between when a task is first trained and after the final task. We plot mean standard error over three seeds, and assess performance across a wide range of memory sizes.

Methods. In addition to our proposed Kprior+EWC+Replay method, we evaluate four relevant baselines for comparison. As our method combines Kprior with both EWC and Replay, we also do ablations to assess the benefit of either term alone. In summary, we consider the following methods:

1. `Kprior+EWC+Replay`. Our proposed regularizer which combines the K-prior function regularizer over M_1 with the EWC-style weight regularizer and the Replay term over M_2.
2. `Kprior`. The original K-prior regularizer over M_1 as proposed by Khan and Swaroop (2021), *without* the EWC-style weight regularization term and *without* the Replay term over M_2.
3. `Kprior+EWC` (ablation). A regularizer combining the K-prior function regularizer over M_1 with *only* the EWC-style weight regularization, i.e. *without* the Replay term over M_2.
4. `Kprior+Replay` (ablation). A regularizer combining the K-prior function regularizer over M_1 with *only* the Replay term over M_2, i.e. *without* the EWC-style weight regularization.
5. `Batch Joint`. Joint batch training of a single multi-head model across the data of all tasks, i.e. the optimal CL solution which serves as an upper bound we wish to approach.
6. `Batch Separate`. Independent batch training of a *separate* model for each task.
7. `Online EWC` (Schwarz et al., 2018), which has the same weight regularizer as Kprior+EWC+Replay, but *without* the function regularizer over M_1 or the Replay term over M_2.

E.2. Results on Split-CIFAR

Setup. Split-CIFAR (Zenke et al., 2017b) has 6 tasks with 10 classes each. The first task is CIFAR-10 (Krizhevsky et al., 2009) with 50,000 training and 10,000 test data points across 10 classes. The subsequent 5 tasks are taken sequentially from CIFAR-100 (Krizhevsky et al., 2009), each with 5,000 training and 1,000 test data points across 10 classes. In total, we thus have 90,000 data points. We use the same CifarNet model as Zenke et al. (2017b);

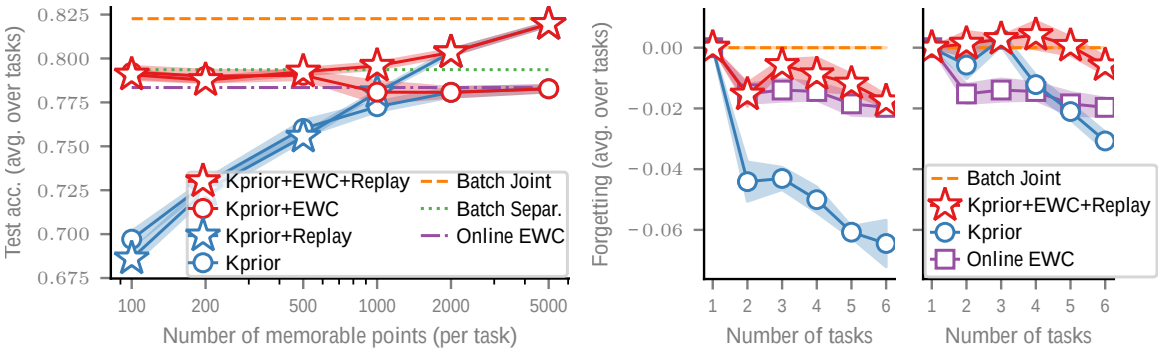

Figure 3: **Results on Split-CIFAR.** Kprior+EWC+Replay is superior across memory sizes, closely approaching Batch Joint for memory size 5,000 (left; x-axis log-scaled). It also forgets less (relative to Batch Joint) with a growing number of tasks, for memory sizes 100 (middle) and 5,000 (right).

Pan et al. (2020): a multi-head CNN with 4 convolutional layers, followed by 2 dense layers with dropout, with 1.2M model parameters in total. On each task, we train for 80 epochs using Adam with learning rate 10^{-3} and batch size 256.

Results. Fig. 3 shows our results on Split-CIFAR. We consider memory sizes between 100 and 5,000 per task; at 5,000, we thus store 10% of the data for task 1, and all data for tasks 2-5. We see that `Kprior` performs poorly at small memory sizes and is much worse than `Online EWC`. While performance improves noticeably with growing memory size, `Kprior` remains far below `Batch Joint` even at memory size 5,000. This confirms that when using a NN instead of a GLM, the theory behind `Kprior` (see Section 3) indeed ceases to hold. However, when we add the Replay term to correct for that error (`Kprior+Replay`), performance is substantially boosted at large memory sizes, actually enabling us to reach `Batch Joint` performance for memory size 5,000. However, the Replay correction term does not help at small memory sizes. In contrast, adding the EWC-style weight regularizer (`Kprior+EWC`) substantially improves performance at small memory sizes, empirically confirming the property that `Kprior+EWC` converges to `Online EWC` for small memories (see Appendix C.1). However, we also confirm that for large memories, `Kprior+EWC` converges to `Kprior`, resulting in a performance drop. Finally, we see that `Kprior+EWC+Replay` combines the complementary benefits of both error correction terms, i.e. of both EWC-style weight-regularization and Replay, to significantly improve upon vanilla `Kprior` in both the small *and* large memory regime. Fig. 3 (mid & right) further shows that our method can leverage prior knowledge more effectively than other methods, thereby suffering less from forgetting with a growing number of tasks. This confirms that the two error correction terms in `Kprior+EWC+Replay` are particularly important for mitigating error accumulation across longer task sequences.

E.3. Results on Split-TinyImageNet

Setup. Following Delange et al. (2021), we construct Split-TinyImageNet by dividing TinyImageNet (Le and Yang, 2015) into a sequence of 10 tasks with 20 classes each (using

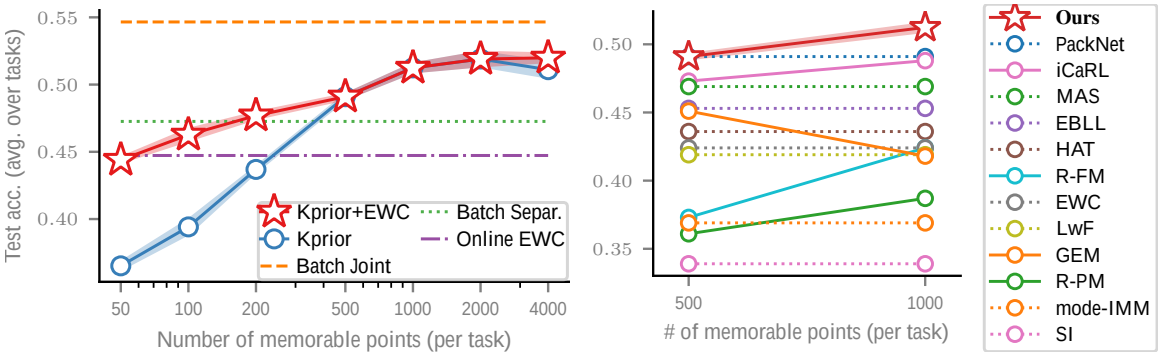

Figure 4: **Results on Split-TinyImageNet.** Kprior+EWC performs well across memory sizes (left; x-axis log-scaled) and compared to further strong baselines from Delange et al. (2021) (right).

the same random division as in Delange et al. (2021)). Each class has 500 data points split into training (80%) and validation (20%), and 50 test points (totalling to 110,000 points). We use the VGG-like BASE model from Delange et al. (2021) with 6 convolutional layers, 4 max pooling layers, and 2 dense layers, with a total of 3.5M parameters. On each task, we train for 70 epochs (with early stopping and exponential learning rate decay, without regularization) using SGD with momentum 0.9 and batch size 200. This replicates the setup of Delange et al. (2021) to make our results directly comparable.[1]

Results. Fig. 4 shows our results on Split-TinyImageNet. We found that the Replay error correction term does not help on this benchmark, so we representatively plot just `Kprior` and `Kprior+EWC`.[2] We again see that `Kprior+EWC` can substantially improve over `Kprior` (especially at small memory sizes) and `Online EWC` (Fig. 4 left). It also compares favourably against a diverse range of other strong CL methods across all three CL paradigms: 1) memory/rehearsal – iCaRL (Rebuffi et al., 2017), GEM (Lopez-Paz and Ranzato, 2017), R-FM & R-PM (Delange et al., 2021), 2) weight-regularization – LwF (Li and Hoiem, 2017), EBLL (Rannen et al., 2017), EWC (Kirkpatrick et al., 2017), SI (Zenke et al., 2017a), MAS (Aljundi et al., 2018), mode-IMM (Lee et al., 2017), and 3) architectural – PackNet (Mallya and Lazebnik, 2018), HAT (Serra et al., 2018) (Fig. 4 right).[3]

Appendix F. Experiment details

For all methods in all experiments, we tuned hyperparameters in the common way by conducting a (exponentially-spaced) grid search and evaluating performance on a held-out validation set. In particular, we tune the following hyperparameters: a temperature parameter

1. The only difference lies in the hyperparameter tuning procedure: while Delange et al. (2021) use their proposed online tuning algorithm, we resort to a standard grid search for simplicity; see Appendix F for details.
2. This is likely because almost perfect train accuracy is attained on all tasks (see e.g. Table 14 in Delange et al. (2021)). Thus, $\boldsymbol{e}^{\text{NN}}$ in Eq. (6) is close to zero, such that NN error correction cannot boost performance.
3. Results are from Delange et al. (2021); their total memory sizes $[4500, 9000]$ equal $[500, 1000]$ per task.

T to scale the logits in the Replay term (as commonly-done in knowledge distillation, see Khan and Swaroop (2021) for a discussion), a trade-off parameter τ in front of the K-prior-style function regularization term, and a trade-off parameter λ in front of the EWC-style weight regularization term.

We used the following tuned values for those hyperparameters: for Split-CIFAR, we have $T = 2.0$ for all methods, $\tau = 0.1$ for Kprior and Kprior+Replay, $\tau = 0.25$ and $\lambda = 2.0$ for Kprior+EWC and Kprior+EWC+Replay, and $\lambda = 10.0$ for Online EWC. For Split-TinyImageNet, we have $T = 1.0$ and $\tau = 16.0$ for all methods. We found that a fixed λ across tasks does not work well for this benchmark, so we tuned a separate λ per task, resulting in the sequence $[330, 85, 45, 30, 20, 15, 10, 10]$ for all methods. In contrast to our grid search procedure, Delange et al. (2021) use a dedicated iterative hyperparameter tuning strategy that trades-off plasticity vs. stability. For ImageNet, we used $T = 1.0$, $\lambda = 1.0$ and $\tau = 0.16$ for all methods.