Few-Shot Unsupervised Continual Learning through Meta-Examples

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Abstract

In real-world applications, data do not reflect the ones commonly used for neural networks training, since they are usually few, unbalanced, unlabeled and can be available as a stream. Hence many existing deep learning solutions suffer from a limited range of applications, in particular in the case of online streaming data that evolve over time. To narrow this gap, in this work we introduce a novel and complex setting involving unsupervised meta-continual learning with unbalanced tasks. These tasks are built through a clustering procedure applied to a fitted embedding space. We exploit a meta-learning scheme that simultaneously alleviates catastrophic forgetting and favors the generalization to new tasks, even Out-of-Distribution ones. Moreover, to encourage feature reuse during the meta-optimization, we exploit a single inner loop taking advantage of an aggregated representation achieved through the use of a self-attention mechanism. Experimental results on few-shot learning benchmarks show competitive performance even compared to the supervised case. Additionally, we empirically observe that in an unsupervised scenario, the small tasks and the variability in the clusters pooling play a crucial role in the generalization capability of the network. Further, on complex datasets, the exploitation of more clusters than the true number of classes leads to higher results, even compared to the ones obtained with full supervision, suggesting that a predefined partitioning into classes can miss relevant structural information.

Introduction

Continual learning has been widely studied in the last few years to solve the catastrophic forgetting problem that affects neural networks. When data are available as a stream of tasks, neural networks tend to focus on the current one, overwriting their weights and consequently causing the forgetting of the previously acquired knowledge that lies in them. Several methods (Kirkpatrick et al. 2016; Lopez-Paz and Ranzato 2017; Chaudhry et al. 2019; Riemer et al. 2019; Zenke, Poole, and Ganguli 2017; Rebuffi et al. 2017) have been proposed to solve this problem involving a replay buffer, network expansion, selectively regularizing and distillation. Some works (Jifel et al. 2019; Vuorio et al. 2018; Rajasegaran et al. 2020; Liu et al. 2020a; Harrison et al. 2020; Yao et al. 2019) take advantage of the meta-learning abilities of generalization on different tasks and rapid learning on new ones to deal with continual learning problems, giving life to meta-continual learning (Javed and White 2019) and continual-meta learning (Caccia et al. 2020). Due to the complex nature of the problem, the proposed approaches generally involve supervised or reinforcement learning settings. Few works on unsupervised meta-learning (Hsu, Levine, and Finn 2019; Khodadadeh, Bölöni, and Shah 2018; Ji et al. 2019) and unsupervised continual learning (Rao et al. 2019) have been recently proposed, but the first ones deal with independent and identically distributed data, while the second one assumes the availability of a huge dataset. Moreover, the majority of continual learning and meta-learning works assume that data are perfectly balanced or equally distributed among classes. We propose a new, more realistic setting dealing with unlabeled and unbalanced tasks in a meta-continual learning fashion and a novel method, namely FUSION-ME (Few-shot Un Supervised CONTinual learning through Meta-Examples) (see Figure 1), that is able to face this complex scenario.

In the task construction phase, rather than directly ex-
Figure 2: Supervised vs unsupervised tasks flow. In the supervised version, tasks are perfectly balanced and contain a fixed number of elements for inner loop (10 samples) and outer loop (15 samples, 5 from the current cluster and 10 randomly sampled from other clusters). In the unsupervised model, tasks are unbalanced and contain $2/3$ of cluster data for the inner loop and $1/3$ for the outer loop in addition to a fixed number of random samples.

exploiting high dimensional raw data, an embedding learning network is used to learn a fitted embedding space to facilitate clustering. Precisely, the k-means algorithm is applied to build tasks composed of unbalanced data, each one with the assigned pseudo-label. Our meta-learning model relies on a double-loop procedure that receives data in an online incremental learning fashion. The classification layers are learned through a single inner loop update, adopting an attentive mechanism that extracts the most relevant features-metan example-of the current unbalanced task; this considerably reduces the training time and memory usage. In the outer loop, to avoid forgetting and improve generalization, we train all model layers exploiting, as input, an ensemble between data of the same class of the stream and data randomly sampled from the overall trajectory (see Figure 2).

We test our model and setup on several datasets, including Omniglot (Lake, Salakhutdinov, and Tenenbaum 2015) and Mini-ImageNet (Deng et al. 2009), achieving favorable results compared to baseline approaches. We also make some preliminary attempts on SlimageNet64 (Antoniou et al. 2020), a novel and difficult benchmark for few-shot continual learning. We show the importance of performing the single inner loop update on the meta-example with respect to both updating over a random sample and updating over multiple samples of the same task. We empirically verify that with tasks generated in an unsupervised manner, the need for balanced data is not crucial compared to the variability in the data and the exploitation of small clusters. To confirm the last statement, we arranged some ablation studies that involve augmentation, varying number of clusters, balancing parameters and comparing a revised version of our model with plain MAML (Finn, Abbeel, and Levine 2017) in a classic meta-learning setting. Summarizing, we can identify three main abilities of our model:

- **adaptation**: the ability to learn from unlabeled and unbalanced tasks and to be adaptable to a more realistic setting with a small loss in performance (unsupervised learning);
- **generalization**: the ability to quickly learn new tasks from few examples (meta/few-shot learning);
- **remembering**: the ability to not forget previously learned tasks (continual learning).

The rest of the paper is organized as follows: first, we present the unbalanced task and the meta-example construction, then we show experimental results obtained with our method compared to baseline approaches. Related works present a literature review on the proposed topic, in particular about continual and meta-learning. Finally, a discussion makes some significant considerations on our current work and anticipates future improvements to our model.

**Unlabeled and Unbalanced Tasks**

We propose a novel method that deals with unsupervised meta-continual learning and study the effect of the unbalanced tasks derived by an unconstrained clustering approach. As done in (Hsu, Levine, and Finn 2019), the task construction phase exploits the k-means algorithm over suitable embeddings obtained through an unsupervised pre-training. This simple but effective method assigns the same pseudo-label to all data points belonging to the same cluster. The first step employs two different models: Deep Cluster (Caron et al. 2018) for Mini-ImageNet and SlimageNet64, and ACAI (Berthelot et al. 2019) for Omniglot. Both these methods consist of unsupervised training and produce an embedding vector set $Z = Z_0, Z_1, ..., Z_N$, where N is the number of data points in the training set. ACAI is based on an autoencoder while Deep Cluster on a deep feature extraction phase followed by k-means clus-
tering. They outline some of the most promising approaches to deal with unlabeled, high dimensional data to obtain and discover meaningful latent features (see Figure 1). Applying k-means over these embeddings leads to unbalanced clusters, which determine unbalanced tasks (see Figure 2). This is in contrast with typical meta-learning and continual learning problems, where data are perfectly balanced. To recover a balanced setting, in (Hsu, Levine, and Finn 2019), the authors set a threshold on the cluster dimension, discarding extra samples and smaller clusters. A recent alternative (Asano, Rupprecht, and Vedaldi 2020) forces the network to balance clusters, but this imposes a partitioning of the embedding space that contrasts with the extracted features. We believe that these approaches are sub-optimal as they alter the data distribution. In an unsupervised setting, where data points are grouped based on the similarity of their features, variability is an essential factor. By keeping also the small tasks, our model generalizes better and reaches higher accuracy at meta-test time. In a data imbalanced setting, the obtained meta-representation is more influenced by large clusters. Since the latter may contain more generic features than the smaller ones, the model is able to generalize better by mostly learning from them. Despite this, the small clusters may contain important information for different classes presented during evaluation. To corroborate this claim, we investigate balancing techniques, both at data-level, such as data augmentation and at model-level, such as balancing parameters into the loss term.

**Few-Shot Continual Learning Architecture**

Our network is composed of a Feature Extraction Network (FEN) and a Classification Network (CLN), both updated during the meta-training phase through a meta-learning procedure based on the construction of a meta-example. MAML and all its variants rely on a two-loop mechanism that allows learning new tasks from a few steps of gradient descent. Recent investigations on this algorithm explain that the real reason for MAML’s success resides in feature reuse instead of rapid learning (Raghu et al. 2020), proving that learning meaningful representations is a crucial factor. Based on this assumption, we focus on the generalization ability of the feature extraction layers. We remove the need for several inner loops, maintaining a single inner loop update through an attentive procedure that considerably reduces the training time and computational resources needed for training the model and increases the global performance. At each time-step, as pointed out in Figure 3, a task $T_i = (S_{\text{cluster}}, S_{\text{query}})$ is randomly sampled from tasks distribution $p(T)$. $S_{\text{cluster}}$ contains elements of the same cluster and is defined as follows:

$$S_{\text{cluster}} = \{(X_k, Y_k)\}_{k=0}^{K}, \text{ with } Y_0 = ... = Y_K,$$

where $Y_0 = ... = Y_K$ is the cluster pseudo-label.

Instead, $S_{\text{query}}$ contains a variable number of elements belonging to the current cluster and a fixed number of elements randomly sampled from all other clusters, and is defined as follows:

$$S_{\text{query}} = \{(X_q, Y_q)\}_{q=0}^{Q}.$$  

![Figure 3: Flow of the CLN parameters update with (green) and without (blue) the use of our meta-example.](image)

All the elements belonging to $S_{\text{cluster}}$ are processed by the frozen FEN, parameterized by $\theta$, computing the feature vectors $R_0, R_1, ..., R_K$ in parallel for all task elements:

$$R_{0:K} = f_\theta(X_{0:K}).$$  

(3)

The obtained embeddings are refined with an attention function parameterized by $\rho$ computes the attention coefficients $\alpha$ from the features vectors:

$$\alpha_{0:K} = \text{Softmax}[f_\rho(R_{0:K})].$$  

(4)

Then, the final aggregated representation learning vector $ME$, called meta-example, captures the most salient features (see Figure 1), and is computed as follows:

$$ME = \sum_{k=0}^{K} [R_k * \alpha_k].$$  

(5)

The single inner loop is performed on this meta-example, which adds up the weighted-features contribution of each element of the current cluster. Then, the cross-entropy loss $\ell$ between the predicted labels and the pseudo-labels is computed and both the classification network parameters $W$ and the attention parameters $\rho$ ($\psi = \{W_i, \rho\}$) are updated as follows:

$$\psi \leftarrow \psi - \alpha \nabla \psi \ell(f_\psi(ME), Y_{0:K}),$$  

(6)

where $\alpha$ is the inner loop learning rate. In Figure 3 we illustrate the CLN parameters update flow. Updating the CLN parameters with multiple-steps, as done in (Javed and White 2019), a single element at a time is processed and the gradient changes with respect to it in an edgy way. Differently, our model takes advantage of meta-examples and leads to a smooth update, approaching the direction indicated by the highest attention coefficients, indicating the most representative samples.

Finally, to update the whole network parameters $\phi = \{\theta, W_i, \rho\}$, and to ensure generalization across tasks, the outer loop loss is computed from $S_{\text{cluster}}$ and $S_{\text{query}}$. The outer loop parameters are thus updated as follows:

$$\phi \leftarrow \phi - \beta \nabla \phi \ell(f_\phi(X_{0:Q}), Y_{0:Q}),$$  

(7)

where $\beta$ is the outer loop learning rate. We report the whole algorithm in Algorithm 1.

At meta-test time, the model is applied to unseen tasks and only the CLN is updated (see Figure 4). We compute the accuracy as it reflects the ability of the model to rapidly learn new tasks and overcome forgetting. Note that with the attention mechanism - exploiting a single inner update - we
remove the unbalancing into the inner loop. Despite that, the representation learning network update remains unbalanced, not affecting the previous considerations about unsupervised meta-learning with unbalanced data.

The FEN is composed of 6 convolutional layers followed by ReLU activations, $3 \times 3$ kernel (for Omniglot, the last one is a $1 \times 1$ kernel) followed by 2 linear layers interleaved by a ReLU activation. The attention mechanism is implemented with two additional linear layers interleaved by a Tanh function and followed by a Softmax and a sum to compute attention coefficients and aggregate features. For Omniglot, we train the model for 40000 steps while for Mini-ImageNet and SlimageNet64 for 200000, with meta-batch size equals to 1. The outer loop learning rate is set to $1e^{-4}$ while the inner loop learning rate is set to 0.01, with Adam optimizer.

### Experiments

#### Datasets

To evaluate our model, we employ two standard datasets typically used to validate few-shot learning methods: Omniglot and Mini-ImageNet. In addition, we try our model on a new and challenging few-shot continual learning benchmark, SlimageNet64. The Omniglot dataset contains 1623 characters from 50 different alphabets with 20 greyscale image samples per class. We use the same splits as [Hsu, Levine, and Finn 2019], using 1100 characters for meta-training, 100 for meta-validation, and 423 for meta-testing. The Mini-ImageNet dataset consists of 100 classes of realistic RGB images with 600 examples per class. As done in [Ravi and Larochelle 2017], [Hsu, Levine, and Finn 2019], we use 64 classes for meta-training, 16 for meta-validation and 20 for meta-test. The SlimageNet64 dataset contains 1000 classes with 200 RGB images per class taken from the down-scaled version of ILSVRC-2012, ImageNet64x64. 800 classes are used for meta-train and the remaining 200 for meta-test purposes. Finally, we use the Cifar100 [Krizhevsky 2009] and Cub [Welinder et al. 2010] datasets to prove our model performance on Out-of-Distribution tasks.

#### Quantitative Results

We present quantitative results, showing how our model behaves in a meta-learning context where data are available incrementally. First, we study data imbalance, then our meta-example based inner loop mechanism to simultaneously process all the elements of the cluster. Subsequently, we investigate how varying the number of clusters affects both performance and generalization capabilities of our model. Finally, we examine the rehearsal strategy in an unsupervised setting and how our model behaves in case of a domain shift. In the tables below, we underline the second-best results when the best does not occur from a single method.

### Balanced vs. Unbalanced Tasks

To justify the use of unbalanced tasks and show that allowing unbalanced clusters is more beneficial than enforcing fewer balanced ones, we present in Table 1 some comparisons achieved on the Omniglot dataset. First of all, we introduce a baseline in which the number of clusters is set to the true number of classes, removing from the task distribution the ones containing less than $N$ elements and sampling $N$ elements from the bigger ones. We thus obtain a perfectly balanced training set at the cost of less variety within the clusters; however, this leads to poor performance as small clusters are never represented. Setting a smaller number of clusters than the number of true classes gives the same results. This test shows that cluster variety is more important than balancing for generalization. To verify if maintaining variety and balancing data can lead to better performance, we try two balancing strategies: augmentation, at data-level, and balancing parameter, at model-level. For the first one, we keep all clusters, sampling $N$ elements from the bigger and using data augmentation for the smaller to reach $N$ elements. At model-level, we multiply the loss term by a balancing parameter, to weight the update for each task based on cluster length. These two tests, especially the latter one, result in lower performance with respect to our FUSION-ME model, suggesting that the only thing that matters is cluster variety. We can also presume that bigger clusters may contain the most meaningful and general features, so unbalancing does not negatively affect the training of our unsupervised meta-continual learning model. Finally, as we want to confirm that this intuition is valid in a more general unsupervised meta-learning model, we perform the balanced/unbalanced experiments also on CACTUs (Hsu, Levine, and Finn 2019). The results are shown in Table 2 (Top) and attest that the model trained on unbalance data outperforms the balanced one, further proving the importance of task variance to better generalize to new classes at meta-test time. We report the results training the algorithms on 20 ways for generality purposes and 5 shots and 15 shots, in order to have enough data points per class to create the imbalance.
Meta-example Single Update vs. Multiple Updates To prove the effectiveness of our method - FUSION-ME - based on meta-examples, we compare it with:

• a revised version - FUSION - that performs multiple updates (one for each element of the cluster);
• a version adopting a single update over a randomly sampled data point from the current task;
• a version exploiting the mean between the feature vector computed from the FEN.

In Table 1, we show that the model trained with the attention-based method consistently outperforms all the other baselines. The single update gives the worst performance, but not really far from the multiple updates one, confirming the idea that the strength of generalization relies on the feature reuse. Also, the mean test has performance comparable with the multiple and single update ones, proving the effectiveness of the attention mechanism to determine a suitable and general embedding vector for the CLN. Training time and resources consumption is considerably reduced with our model based on a single update on the generated meta-example (see Supplementary Material). We also test our technique in a standard meta-learning setting. We apply our meta-example update to MAML (Finn, Abbeel, and Levine 2017) on Omniglot dataset in Table 1 (bottom), consistently outperforming it. We report the results training on 20 ways and 1 and 5 shots. In particular, the 5 shots test highlights the effectiveness of our aggregation method.

FUSION-ME vs. Oracles To see how the performance of FUSION-ME is far from those achievable with the real labels, we also report for all datasets the accuracy reached in a supervised setting (oracles). We define Oracle OML the supervised model present in (Javed and White 2019), and Oracle OML-ME the supervised model updated with our meta-example strategy. Oracle OML-ME outperforms Oracle OML on Omniglot, Mini-ImageNet, and SlimageNet64, suggesting that the meta-examples strategy is beneficial even in a fully supervised case. FUSION-ME reaches higher performance compared to the other FUSION baselines but lower - on Omniglot - or not so far - on SlimageNet64 - compared to the Oracle OML. On Mini-ImageNet, our model trained with 256 clusters outperforms both oracles.

To further improve the performance avoiding forgetting at meta-test time, we add a rehearsal strategy based on reservoir sampling on the CLN (FUSION-ME RS). This generally results in superior performance on Omniglot. On Mini-ImageNet the performance with and without rehearsal are similar, due to the low number of test classes in the dataset that alleviates catastrophic forgetting.

Number of Clusters In an unsupervised setting, the number of original classes could be unknown. Consequently, it is important to assess the performance of our model by varying the number of clusters at meta-train time. With a coarse-grain clustering, a low number of clusters are formed and distant embeddings can be assigned to the same pseudo-label, grouping classes that can be rather different. On the other hand, with a fine-grain clustering, a high number of clusters with low variance are generated. Both cases lead to poor performance at meta-test time.

We test our model on Omniglot (see Table 1) setting the number of clusters to:

• the true number of classes (FUSION);
• a lower number of clusters (FUSION balanced 500), resulting in more than 20 samples each.

Since the Omniglot dataset comprehends 20 samples per class, in the first case it results in unbalanced tasks, while in the second we sample 20 elements from the bigger clusters. The performance of the 1100 clusters test is consistently higher than that obtained with the 500 clusters test, confirming that variability is more important than balancing.
On Mini-ImageNet, we test our method with 64, 128, 256, and 512 clusters (FUSION-ME number of clusters). Since Mini-ImageNet contains 600 examples per class, after clustering we sample examples between 10 and 30, proportionally to the cluster dimension. We obtain the best results with 256 clusters and the meta-example approach, outperforming not only the other unsupervised experiment but also the supervised oracle, on all class incremental settings. Also, with SlimImageNet64, the best results are obtained with 1600 clusters (see Table 4). This finding suggests that, with complex datasets, the number of clusters is crucial to reach higher meta-test performance and to find general features. With the correct number of clusters, we are capable of grouping meaningful features together, allowing the model to reach, with the subsequent meta-continual training, a representation that generalizes better at meta-test time. To corroborate the above findings, we observe that using 512 clusters degrades performance with respect to the 256 case, suggesting that tasks constructed over an embedding space with too specific features fail to generalize. Using a lower number of clusters, such as 64 or 128, also achieves worse performance. This time, the embedding space is likely aggregating distant features, leading to a complex meta-continual training, whose pseudo-classes are not clearly separated.

**Out-of-Distribution Tasks** Since our model is unsupervised, FEN training is only based on feature embeddings, with no class-dependent bias. This way, our model could be general enough for OoD tasks, where the training tasks belong to a different data distribution (i.e., a different dataset) with respect to the test tasks. To investigate this conjecture, we test our model on the Cifar100 and Cub datasets. Results in Table 5 show that, by training on Mini-ImageNet and testing on Cifar100 (top half) or training on Omniglot and testing on Cub (bottom half), the unsupervised approach generally outperforms the supervised one. In the latter case, FUSION-ME also outperforms the supervised oracle trained on Cub, which is incapable of learning a meaningful representation in our particular setting.

### Related Work

Unsupervised meta-continual learning involves many open research problems that are nowadays studied separately. In this section, we provide a brief introduction to the state-of-the-art on individual fields and how they were recently merged to allow solutions to be adaptable to realistic contexts.

### Continual Learning

Continual learning is one of the most challenging problems arising from neural networks that are heavily affected by catastrophic forgetting. The proposed methods can be divided into three main categories: architectural strategies, regularization strategies and rehearsal strategies. Architectural strategies are based on specific architectures, layers, activation functions, or weight-freezing methods designed to mitigate catastrophic forgetting (Rusu et al. 2016; Schwarz et al. 2018). Regularization strategies are based on putting regularization terms in the loss function, promoting selective consolidation of important past weights (Kirkpatrick et al. 2016; Zenke, Poole, and Ganguli 2017). Rehearsal strategies focus on retaining part of past information and periodically replaying it to the model to strengthen connections for memories. The basic idea is to store a limited amount of information of the past and then add a further term to the loss that takes into account loss minimization on the buffer data, besides the current data. Several works have been proposed in this direction involving meta-learning (Riemer et al. 2019; Spigler 2019), combination of rehearsal and regularization strategies (Lopez-Paz and Ranzato 2017; Chaudhry et al. 2019), knowledge distillation (Furlanello et al. 2018; Li and Hoiem 2018; Hou et al. 2018; Lee et al. 2019), generative replay (Shin et al. 2017; Silver and Mahluz 2020; Liu et al. 2020) and channel gating (Abati et al. 2020).

### Unsupervised Continual Learning

Only a few recent works have studied the problem of unlabeled data, which mainly involves representation learning. Previously, iCaRL (Rebuffi et al. 2017) introduces a method involving a representation learning network and an incremental classifier in a supervised setting, resembling the idea proposed by unsupervised methods. CURL (Rao et al. 2019) proposes an unsupervised model built on a representation learning network. This latter learn a mixture of Gaussian encoding task variations, then integrates a generative memory replay buffer as a strategy to overcome forgetting.

### Meta-Learning

Meta-learning, or learning to learn, aims to improve the neural networks ability to rapidly learn new tasks with few training samples. The majority of meta-learning approaches proposed in literature are based on Model-Agnostic Meta-Learning (MAML) (Finn, Abbeel, and Levine 2017; Re-
Meta-learning has extensively been merged with continual learning for different purposes. We can highlight the existence of two strands of literature \cite{Caccia et al. 2020; meta-continual learning} with the aim of incremental task learning and continual-meta learning with the aim of fast remembering. Continual-meta learning approaches mainly focus on making meta-learning algorithms online, with the aim to rapidly remember meta-test tasks. Online meta-learning \cite{Finn et al. 2019} is an online version of MAML, with the limitation of not considering the catastrophic forgetting problem. In \cite{Jernite et al. 2019}, the authors propose a Dirichlet process mixture of hierarchical Bayesian models that is able to deal with a potentially infinite mixture in a continual learning fashion. MOCA \cite{Harrison et al. 2020} extends meta-learning to operate with a stream of tasks, finding the change of task though an online changepoint analysis. More relevant to our work are meta-continual learning algorithms \cite{Vuorio et al. 2018; Javed and White 2019; Beaulieu et al. 2020; Yao et al. 2019}, which use meta-learning rules to “learn how not to forget”. OML \cite{Javed and White 2019} and its variant ANML \cite{Beaulieu et al. 2020} favor sparse representations by employing a trajectory-input update in the inner loop and a random-input update in the outer one. The algorithm jointly trains a representation learning network (RLN) and a prediction learning network (PLN) during the meta-training phase. Then, at meta-test time, the RLN layers are frozen and only the PLN is updated. ANML replaces the RLN network with a neuro-modulatory network that acts as a gating mechanism on the PLN activations following the idea of conditional computation. HSML \cite{Yao et al. 2019} is a hierarchically structured approach to meta-continual learning involving a hierarchical task clustering strategy to resemble the human brain’s way to associate knowledge. Other works, such as \cite{Liu et al. 2020a; Rajasegaran et al. 2020; Tao et al. 2020} focus on incrementally learning new tasks in a few-shot setting, respectively through a metric-based, a task-agnostic learner and a neural gas network.

**Discussion**

In this work, we tackle a novel problem concerning few-shot unsupervised continual learning. We propose a simple but effective model based on the construction of unbalanced tasks and meta-examples.

Our model is motivated by the power of representation learning, which relies on few and raw data with no need for human supervision. With an unconstrained clustering approach, we find that no balancing technique is necessary for an unsupervised scenario that needs to generalize to new tasks. In fact, the most robust and general features are gained though task variety; even if favoring larger clusters leads to more general features, smaller ones should not be discarded as they can be representative of less common tasks. This means that there is no need for complex representation learning algorithm that try to balance clusters elements. A future achievement is to deeply investigate this insight by observing the variability of the embeddings in the feature space. Our model overcomes the principal limitations of meta-continual learning approaches, reaching favorable results also when facing OoD task, often better than the ones obtained with supervised approaches. A further improvement consists in the introduction of FiLM layers \cite{Perez et al. 2017; Zintgraf et al. 2019; Tseng et al. 2020} into the FEN to change data representation at meta-test time and the introduction of an OoD detector to find OoD tasks and change the model behavior. The performances of our model with meta-examples suggest that a single inner update can in-
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Few-Shot Unsupervised Continual Learning through Meta-Examples
(Supplementary Material)

Rehearsal at Meta-Train Time

Rehearsal strategy can be useful at meta-test time. In particular, when the CLN is adapted to new tasks in an incremental fashion, its weights can be overridden favoring the last tasks at the expense of the first ones. The beneficial effect of rehearsal at meta-test time can be noticed when the number of test tasks is high. In fact, reservoir sampling is generally helpful on Omniglot, that is tested on 200 classes, while it does not give the same benefit on Mini-ImageNet, where it reaches similar or a little lower performance.

We want to verify if rehearsal can be beneficial also at meta-train time, replacing the query set $S_{query}$ with a core-set built with reservoir sampling $S_{coreset}$. This way, instead of sampling from random clusters, a buffer of previously seen data is stored in a buffer of fixed dimension. We try three different memory size 200, 500, 1000, obtaining, as expected, increasing results as the size increases.

In Table 6, we report accuracy results on Omniglot adding rehearsal only at meta-train time, and adding it at both meta-train and meta-test time with FUSION and FUSION-ME. We report only the results obtained with a buffer size 500 to avoid redundancies. As it can be noted, with FUSION, using a core-set instead of a query set at meta-train time increases the performance with respect to the case of query set usage, meaning that the representation suffers from catastrophic forgetting and the use of random data (acting only for generality purposes and not contrasting forgetting) are not enough to learn a good representation. On the contrary, with FUSION-ME, the use of a rehearsal strategy at meta-train time get worse performance. We hypothesize that this behavior is due to the different number of inner loop update between the two models. In fact, FUSION, making several inner loop updates on data belonging to the same cluster, brings the CLN weights nearest the current cluster, suffering the effect of forgetting more then FUSION-ME that makes a single inner loop on the meta-example. These results prove that, at meta-train time, FUSION-ME needs only the generalization ability given by $S_{query}$, while FUSION needs also the remembering ability given by $S_{coreset}$.

Details on Balancing Techniques

Table 6: Meta-test test results on Omniglot dataset with rehearsal only during meta-test and both at meta-train and meta-test.

| Algorithm/Classes | 10  | 50  | 75  | 100 | 150 | 200 |
|-------------------|-----|-----|-----|-----|-----|-----|
| FUSION RS only test | 67.9 | 55.1 | 46.2 | 37.0 | 29.6 | 25.6 |
| FUSION RS both train/test | 75.9 | 56.8 | 51.2 | 39.7 | 30.5 | 25.0 |
| FUSION-ME RS only test | 81.6 | 56.4 | 54.0 | 44.6 | 34.1 | 27.4 |
| FUSION-ME RS both train/test | 74.7 | 47.0 | 48.4 | 38.3 | 28.9 | 24.2 |

Data Augmentation

We apply data augmentation on the Omniglot dataset to observe if balancing the clusters could lead to superior performance. We notice that the results reached applying data augmentation are comparable with the one obtained with unbalanced tasks. Practically, we sample 20 elements from the clusters bigger than 20, while we exploit augmentation on the cluster with less than 20 elements. Till reaching 20 samples for tasks, we pick each time a random image between the ones in the cluster employing a random combination of various augmentation techniques, such as horizontal flip, vertical flip, affine transformations, random crop, and color jitter. In detail, about the random crop, we select a random portion included between 75%, 80%, 85%, or 90% of the entire image. Regarding the color jitter, we use brightness, contrast, saturation, and hue factor (the first three denote a factor including between 0.8 and 1.2, the hue instead one including between −0.02 and 0.02) to adjust the image.

Loss Balancing

Our model applies clustering on all training data before starting to learn the meta-representation. This way, we can find the maximum $C_{\max}$ and minimum number $C_{\min}$ of elements per cluster obtained by k-means algorithm. Then, for each cluster, we find its number of elements $C_{current}$ and compute the balanced vector $\Gamma$ as follow.

$$\Gamma = \frac{C_{\max} - C_{\min}}{C_{current} - C_{\min} + \epsilon},$$  \hspace{1cm} (8)

where $\epsilon$ is used to avoid division by zero. Finally $\Gamma$ is normalized as follow.

$$\Gamma_{\text{norm}} = \frac{\Gamma - \Gamma_{\min}}{\Gamma_{\max} - \Gamma_{\min}},$$ \hspace{1cm} (9)

For each sampled task (taskId), the corresponding balancing parameter is selected and multiplied by the cross-entropy loss $CE$ during meta-optimization as reported in below.

$$L = \Gamma_{\text{norm}}[\text{taskId}] \cdot CE(\text{logits}, Y),$$ \hspace{1cm} (10)

where logits indicate the output of the model.
Sinkhorn-Knopp algorithm is applied. Larger datasets. To solve this problem a fast version of the algorithm is introduced, extending standard cross-entropy minimization to an optimization objective defined as:

\[
\min_{p,q} E(p,q) \\
\text{subject to } \forall y : q(y|x_i) \in \{0,1\} \text{ and } \sum_{i=1}^{N} q(y|x_i) = \frac{N}{K}.
\]

\(E(p,q)\) is defined as the average cross-entropy loss, while the constraints mean that the \(N\) data points are split uniformly among the \(K\) classes and that each \(x_i\) is assigned to exactly one label. The objective in Equation (11) is solved as an instance of the optimal transport problem, for further details refer to the paper.

DeepCluster adopts particular implementation choices to avoid degenerate solutions, but contrary to SeLa it does not force the clusters to contain the same number of samples. We empirically observe that in our setting an unconstrained approach leads to better results.

### Time and Computational Analysis

In Table 8 we compare training time and computational resources usage between FUSION and FUSION-ME on Omniglot and Mini-ImageNet. Both datasets confirm that FUSION-ME, adopting a single inner update, trains considerably faster and uses approximately one-third of the GPU resources with respect to FUSION. This latter performs an update for each sample included in \(S_{\text{cluster}}\), keeping a computational graph of the model in memory for each update. This leads to slower training time, especially when the required number of epochs is high, such as for Mini-ImageNet. Even though with this kind of datasets we do not require particular GPU resources, this test shows the strength of our model in an eventually future scenario exploiting large image, deeper network, and more cluster samples.

### Learning in the Jungle

To the best of our knowledge, a few-shot unsupervised continual learning setting has never been studied before in the literature. However, some works propose “learning in the jungle” problems, that involve a mixture of non-trivial settings. In Table 9 we compare some novel methods to our FUSION-ME, highlighting the features of each one. Our model is the only one that presents such complex setting involving few-shot learning, continual learning, unlabelled and unbalanced tasks and proposes experiments that show the model ability to learn from OoD data. Note that this analysis is not intended to be a complete analysis of all the methods of continual learning and few-shot learning, but only of those that have been placed in a different setting from the one that is commonly used in these two fields or that are related to them.

### FiLM Layers for OoD Tasks

To further improve the results testing on OoD tasks, we introduce FiLM (Perez et al. [2017]) layers within the OML architecture (the supervised baseline). In a FiLMed neural network some conditional input is used to conditioned FiLM layers, to influence the final prediction by this input. The FiLM generator map this information into FiLM parameters, applying feature-wise affine transformation (in particular scaling and shifting) element-wise (features map-wise for CNN). If \(x\) is the input of a FiLM layer, \(z\) a conditional input, and \(\gamma\) and \(\beta\) are \(z\)-dependent scaling and shifting vectors, the FiLM transformation is reported below.

\[
\text{FiLM} = \gamma(z)x \odot \beta(z)
\]

We apply this concept to OML, conditioning the prediction to task-specific features. We add two FiLM layers as linear layers after each of the last two convolutional layers of the FEN. These layers have adaptable parameters, updating in both the inner and the outer loop. In detail, recovering
Table 9: Features comparison between our FUSION-ME and several works recently proposed in the literature involving continual learning and few-shot learning into the wild.

| Few-shot | Unsupervised | Continual | Imbalance | OoD | Algorithm                        |
|----------|--------------|-----------|-----------|-----|----------------------------------|
| ✓        | ✓            | ✓         | ✓         | ✓   | iCARL (Rebuffi et al. 2017)      |
| ✓        | ✓            | ✓         | ✓         | ✓   | CURL (Kao et al. 2019)           |
| ✓        | ✓            | ✓         | ✓         | ✓   | CACTUS (Hsu, Levine, and Finn 2019) |
| ✓        | ✓            | ✓         | ✓         | ✓   | UMTRA (Khodadadeh, Bólóni, and Shah 2018) |
| ✓        | ✓            | ✓         | ✓         | ✓   | UFLST (Ji et al. 2019)           |
| ✓        | ✓            | ✓         | ✓         | ✓   | L2B (Lee et al. 2020)            |
| ✓        | ✓            | ✓         | ✓         | ✓   | OML (Javed and White 2019)       |
| ✓        | ✓            | ✓         | ✓         | ✓   | ANML (Beaulieu et al. 2020)      |
| ✓        | ✓            | ✓         | ✓         | ✓   | Continual-MAML (Caccia et al. 2020) |
| ✓        | ✓            | ✓         | ✓         | ✓   | iTAML (Rajasegaran et al. 2020)   |
| ✓        | ✓            | ✓         | ✓         | ✓   | FUSION-ME (Ours)                 |

Table 10: Meta-test test results on Omniglot dataset with FiLM layers applied on Oracle OML.

| Algorithm/Classes | 10 | 50 | 75 | 100 | 150 | 200 |
|-------------------|----|----|----|-----|-----|-----|
| Oracle OML        | 88.4 | 74.0 | 69.8 | 57.4 | 51.6 | 47.9 |
| OML FiLM          | 91.1 | 79.5 | 80.6 | 68.6 | 64.0 | 52.7 |

what was already done in (Zintgraf et al. 2019), we introduce a 100-dimensional context parameter vector producing, through the linear layer, 512 filters. These filters are used to apply an affine transformation on the output of the convolutional layer. Context parameters are reset to zero before each new task, while FiLMs are trained to be general for all tasks and never reset during meta-train.

At meta-test time, we update the FiLM layers (during the meta-test train phase) and we reset the context parameters after each new task. This way, the context parameters are specific and dependent on each task while the FiLM layers can adapt themselves to the new unseen classes, in order to shift the frozen representation according to the context. This way, if a task changes, the model could be able to shift the representation reaching better generalization capabilities. The advantage is more pronounced facing with OoD tasks since their distribution is much different with respect to the meta-train one. We report some preliminary results obtained applying FiLM layers on the OML (Javed and White 2019) model, trained on Omniglot and tested on both Omniglot (see Table 10) and Cifar100 (see Table 11). We find that OML with FiLM layers outperforms or at least equals on both dataset.

The results are promising, but we believe that much better performance could be achieved training context parameters and FiLM layers separately or introducing some tricks to train them together.

**The Effect of Self-Attention**

Here we want to empirically view how our self-attention mechanism acts on cluster images. We report some examples of clusters and the respectively self-attention coefficients that FUSION-ME associates to each image. In Figure 4 and Figure 5, some samples obtained during FUSION-ME training are reported, on Mini-ImageNet and Omniglot respectively. The darker colors indicate the values of the highest attention coefficient, while the lighter colors indicate the lower ones. In the majority of cases, our mechanism rewards the most representative examples of the cluster, meaning the ones that globally contain most of the features present in the other examples as well. A further improvement could be to identify the outliers (the samples more distant from the others at features-level) of a cluster and discard them before the self-attention mechanism is ap-
Figure 5: Samples of clusters (one for each row) generated on Omniglot. Self-attention coefficients are reported associated to each image.

...plied. This way, only the features of the correctly grouped samples can be employed to build the meta-example.