Online Fast Adaptation and Knowledge Accumulation: 
a New Approach to Continual Learning

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Abstract
Learning from non-stationary data remains a great challenge for machine learning. Continual learning addresses this problem in scenarios where the learning agent faces a stream of changing tasks. In these scenarios, the agent is expected to retain its highest performance on previous tasks without re-visiting them while adapting well to the new tasks. Two new recent continual-learning scenarios have been proposed. In meta-continual learning, the model is pre-trained to minimize catastrophic forgetting when trained on a sequence of tasks. In continual-meta learning, the goal is faster remembering, i.e., focusing on how quickly the agent recovers performance rather than measuring the agent’s performance without any adaptation. Both scenarios have the potential to propel the field forward. Yet in their original formulations, they each have limitations. As a remedy, we propose a more general scenario where an agent must quickly solve (new) out-of-distribution tasks, while also requiring fast remembering. We show that current continual learning, meta learning, meta-continual learning, and continual-meta learning techniques fail in this new scenario. Accordingly, we propose a strong baseline: Continual-MAML, an online extension of the popular MAML algorithm. In our empirical experiments, we show that our method is better suited to the new scenario than the methodologies mentioned above, as well as standard continual learning and meta learning approaches.

1. Introduction
A common assumption in machine learning is that the input to a learning algorithm consists of independent and identically distributed (i.i.d.) data. This assumption is violated in many practical applications handling non-stationary data distributions, including robotics, autonomous driving cars, conversational agents interacting with different people at different times, and other real-time applications, from sensor data analysis to stock market prediction, to name a few. Over the last few years, several methodologies were developed that relax the i.i.d. assumption. We focus on Continual learning (CL), where the goal is to learn incrementally from a non-stationary data sequence involving different datasets or tasks, while not forgetting previously acquired knowledge – in other words, to overcome the problem known as catastrophic forgetting (McCloskey & Cohen, 1989). In particular, we address the scenario wherein an autonomous system, embedded or not, is deployed in environments or domains that might differ from the one it was pre-trained on. Thus, the system must adapt and learn in an online fashion such that its cumulative rewards are maximized (Kaelbling, 1991; 1993).

Continual learning is useful in various learning scenarios (Farquhar & Gal, 2018)–unsupervised, supervised, and especially reinforcement learning, where the observed data can vary a lot between different locations in the environment (Kaelbling et al., 1996). supervised continual learning has become the most active area of recent CL research. Compared to reinforcement learning, it is much easier to study the forgetting problem in isolation when there is no credit assignment problem. As for unsupervised learning, finding good evaluations metric is still an open problem. Furthermore, supervised learning problems usually require less compute and memory resources, which enables researchers to iterate faster and lowers the bar entry. Accordingly, we keep the focus on supervised CL.

A common supervised CL scenario is task-incremental classification, where classification datasets are presented to an online learner sequentially, one task at a time. For each task T_i at iteration t, the data are sampled i.i.d. from their corresponding probability distribution P_t(x, y). The model must adapt to new tasks, learning to perform accurate classifications on them, while still retaining its predictive performance on previously learned tasks. In other words, CL methods are often evaluated using their (average) perfor-
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In this paper, we expand the above CL frameworks towards a more flexible and general scenario—which is designed to be better suited for many challenging real-life applications. We imagine an agent, embedded or not, first pre-trained in a controlled environment and later deployed in the real world, where it faces new or unexpected situations. This scenario is relevant for many applications. For instance, in robotics, the agent is pre-trained in a factory and deployed in homes or in manufactures where it will need to adapt to new domains and maybe solve new tasks. Likewise, a virtual assistant can be pre-trained on static datasets and deployed in a user’s life to fit its personal needs. Further motivations can be found in time series forecasting, e.g., market prediction, game playing, autonomous customer service, recommendation systems, autonomous driving, to name a few. In this scenario, we are interested in the cumulative performance of the agent throughout its lifetime, as advocated in Kaelbling (1991; 1993). Differently, standard CL reports the agent’s final performance on all tasks at the end of its life. In order to succeed in this scenario, agents need the ability to learn new tasks as well as quickly remembering old ones.

We name our CL setting *Online faSt Adaptation and Knowledge Accumulation (OSAKA)*. The main characteristics of OSAKA are: at deployment or CL time, (1) tasks shifts are sampled stochastically and (2) the task boundaries are unknown (*task-agnostic* setting), (3) multiple levels of non-stationarity are used, and (4) tasks can be revisited. Furthermore, our evaluation of CL performance is different from the one commonly used in CL. We report the cumulative or online average performance instead of the final performance on all seen tasks.

Existing CL methods are not well-suited to OSAKA. Most methods, such as EWC (Kirkpatrick et al., 2017), progressive networks (Rusu et al., 2016), or MCL (Javed & White, 2019), require task boundaries. On the other hand, task-agnostic methods such as Aljundi et al. (2017); Zeno et al. (2018); He et al. (2019) optimize for the final performance of the model and thus resort to mechanisms that alleviate catastrophic forgetting. These added computations not only hinder online performance but unnecessarily increases the computation footprint of the algorithms.

To address the challenges of OSAKA we propose *Continual-MAML*, a baseline inspired by the meta-learning approach of MAML (Finn et al., 2017). The proposed method is pre-trained via meta learning. When deployed, Continual-MAML adapts the learned parameter initialization to solve new tasks. When a change in the distribution is detected, new knowledge is incorporated into the learned initialization. As a result, the proposed algorithm is both efficient and robust to distribution changes since it does not require computationally expensive optimizers like BGD (Zeno et al., 2018) or replay methods used in prior work (Chaudhry et al., 2018; Shin et al., 2017).

Using our OSAKA scenario, we compare the performance of Continual-MAML to recent and popular approaches from continual learning, meta learning, and continual-meta learning. Across several datasets, we observe that Continual-MAML is better suited to OSAKA than prior methods from the aforementioned fields and thus provides an initial baseline.
To summarize, our contributions include: (1) OSAKA, a new CL setting which is more flexible and general than previous ones. Related, we also propose a unifying scenario for discussing meta- and continual learning scenarios (Table 1); (2) the Continual-MAML algorithm, a new baseline that addresses the challenges of the OSAKA setting; (3) extensive empirical evaluation of our proposed method and the current literature in this new scenario; and (4) a codebase\(^1\) for researchers to test their methods in the OSAKA scenario.

## 2. Related Work

Our method intersects the topics of continual learning, meta learning, continual-meta learning, and meta-continual learning. For each of these topics, we describe the related work and current state-of-the-art methods. We highlight their differences in Table 7.

### Continual learning

Given a non-stationary data stream, standard learning methods such as stochastic gradient descent (SGD) are prone to catastrophic forgetting as the network weights adapted to the most recent task quickly cannot perform the previous ones anymore. Many continual learning approaches have been proposed in recent years, which can be roughly clustered into: (1) replay-based methods, (2) regularization-based methods, and (3) parameter-isolation methods. **Replay-based** methods store representative samples from the past, either in their original form (e.g., *rehearsal methods* (Rebuffi et al., 2017; Isele & Cosgun, 2018; Rolnick et al., 2019; Aljundi et al., 2019a), **constrained optimization** based on those samples (Lopez-Paz & Ranzato, 2017)), or in a compressed form, e.g., via a generative model (Aljundi et al., 2019a; Caccia et al., 2019; Ostapenko et al., 2019; Lesort et al., 2019a). However, those methods require additional storage, which may need to keep increasing when the task sequence is longer. **Regularization-based or prior-based** approaches (Kirkpatrick et al., 2017; Nguyen et al., 2018; Zeno et al., 2018) prevent significant changes to the parameters that are important for previous tasks. Most prior-based methods rely on task boundaries. However, they fail to prevent forgetting with long task sequences or when the task label is not given at test time (Farquhar & Gal, 2018; Lesort et al., 2019c). The third family, *parameter isolation* or *dynamic architecture* methods, attempts to prevent forgetting by using different subsets of parameters for fitting different tasks. This is done either by freezing the old network (Xu & Zhu, 2018; Serrà et al., 2018) or growing new parts of the network (Lee et al., 2017; Schwarz et al., 2018). Dynamic architecture methods, however, usually assume that the task label is given a test time, which reduces their applicability in real-life settings.

**Meta learning.** Learning-to-learn methods are trained to infer an algorithm that adapts to new tasks (Schmidhuber, 1987). Meta learning has become central for few-shot classification (Ravi & Larochelle, 2016; Vinyals et al., 2016; Oreshkin et al., 2018). A commonly used meta-learning algorithm is MAML (Finn et al., 2017), which optimizes the initial parameters of a network such that adapting to a new task requires few gradient steps. ANIL (Raghu et al., 2019) is another variation of meta learning that requires only adapting the network’s output layer or head to the new tasks. These algorithms leverage gradient descent to learn a feature representation that is common among various tasks, but they are not suitable when the new tasks have a drastic distribution shift from the existing tasks. Despite the limitations of meta-learning methods, they can be adapted to address the challenges of continual learning, as we will describe below.

**Meta-continual learning.** Since non-stationary data distributions breaks the i.i.d assumption for SGD, it is natural to consider continual learning as an optimization problem where the learning rule learns with non-stationary data. Therefore, some recent works focus on learning a non-forgetting learning rule with meta learning, i.e., meta-continual learning.

In Javed & White (2019), the model is separated into a representation learning network and a prediction learning network. The representation learning network is meta learned so that the prediction learning part can be safely updated with SGD without forgetting. In Vuorio et al. (2018), a gradient-based meta-continual learning is proposed. The update is computed from a parametric combination of the gradient of the current and previous task. This parametric combination is trained with a meta objective that prevents forgetting.

These approaches are all limited by the fundamental assumption of meta learning that the distribution of the meta testing set matches that of the meta training set. Thus it is not guaranteed that the meta-learned representation or update rule is free of catastrophic forgetting when OoD data is encountered in the future. Despite that, meta-continual learning is actively researched (Riemer et al., 2018; Beaulieu et al., 2020).

**Continual-meta learning.** Recently, several methods emerged that address the continual-meta learning setup. FTML (Finn et al., 2019) extends the MAML algorithm to the online learning setting by incorporating the follow the leader (FTL) algorithm (Hannan, 1957). FTL provides an $O(\log T)$ regret guarantee and has shown good performance on a variety of datasets. Dirchlet-based meta learning (DBML) (Jerfel et al., 2019) uses a Dirchlet mixture model to infer the task identities sequentially.

\(^1\)https://github.com/ElementAI/osaka
More relevant to our work, MetaBGD (He et al., 2019) addresses the problem of fast remembering when the task segmentation is unavailable. MOCA (Harrison et al., 2019) extends meta-learning methods with a differentiable Bayesian change-point detection scheme to identify whether a task has changed. They, however, explore the setting where tasks never re-occur.

### 3. Online Fast Adaptation and Knowledge Accumulation

We now discuss our proposed setting OSAKA for continual learning. We first describe the non-stationary data generation process in Section 3.1, then we introduce a unifying framework to characterize meta learning, continual learning, and i.i.d. learning paradigms in Section 3.2. In Section 3.3, we explain, motivate, and justify our setting.

#### 3.1. Data generation

We assume there is a hidden context variable $C$ that determines the data distribution, which could represent, e.g., the current mood of a user for a recommender system or an opponent’s strategy in game playing. Given the context, data can be sampled i.i.d. from $p(X|C)$. Let $W$ denote a finite set of all possible contexts. Different learning paradigms can be described by specializing the distribution $P(C)$. In the classical setting data are sampled i.i.d. from $p(X|C)P(C)$ where $C$ could represent classes. In meta learning, $C$ represents the task descriptor or task label, and both meta-training and meta-testing sets are sampled i.i.d. from $P(C)$. E.g., applied to N-shot classification, the task descriptor would specify the N classes which have to be discriminated against. In continual learning, the data distribution is non-stationary, and various CL scenarios arise from specific assumptions about this non-stationarity. Here we assume that data non-stationarity is caused by a hidden process \{C_t\}_{t=1}^T, where $C_t$ is the context at time $t$. C in continual learning can be the task label, e.g., in Permuted MNIST, disjoint MNIST/CIFAR10 (Kirkpatrick et al., 2017). It could also be the class label in the incremental classification setting (Rebuffi et al., 2017). \{C_t\}_{t=1}^T is usually assumed to be an ordered list of the tasks/classes.

#### 3.2. Unifying the frameworks

We propose a unifying notation to highlight the differences between several relevant machine-learning paradigms. In particular, we compare continual learning with meta-continual learning, continual-meta learning, meta learning, and supervised learning (summarized in Table 1).

We use a support set $S$ and a query set $Q$ to denote the training and test sets of the inner loop (Vinyals et al., 2016), respectively. These sets are usually composed of $n$ i.i.d. samples $X_i = (x_i, y_i)$, generated conditionally from the context $C$. We define our learning algorithm $A$ as a function taking a support set $S$ as input and returning a predictor $f_\theta$, where $\theta$ are the parameters describing the behavior of the predictor, i.e. $f_\theta = A(S)$. Next, a loss function $\mathcal{L}(f_\theta, Q)$ is used to evaluate the predictor $f_\theta$ on the query set $Q$.

A meta-learning algorithm $A_\phi$ adapts its behavior by learning the parameters $\phi$. It samples $M$ i.i.d. pairs of support and query sets from a distribution over contexts: $\{C_i\}_{i=1}^M \sim \mathcal{W}^M$, and $(S_i, Q_i) \sim C_i$. Assuming that the learning process is differentiable, the parameters $\phi$ can be adjusted using the gradient from evaluation on the query set, $\nabla_\phi \mathcal{L}(A_\phi(S_i), Q_i)$. For a valid final evaluation, the learning of $\phi$ is done on the sets $(S_i, Q_i)$, where $i < N < M$ and the evaluation is done using $\sum_{i=N}^M \mathcal{L}(A_\phi(S_i), Q_i)$.

Continual-learning algorithms work with a sequence of support sets, $S_{1:T}$, and a sequence of query sets, $Q_{i:1:T}$, obtained from a sequence of contexts, $C_{1:T}$. A continual learning algorithm CL transforms the sequence $S_{1:T}$ into a predictor $f_\theta$ i.e. $f_\theta = CL(S_{1:T})$. The main difference with a conventional algorithm $A$ is that the support set is observed sequentially and cannot be fully stored in memory. The evaluation is then performed independently on each query set $Q_t$ (obtained in the same context as $S_t$), i.e. $\sum_{t=1}^T \mathcal{L}(f_\theta, Q_t)$.

Meta-continual learning combines meta-learning and continual learning. A collection of $M$ sequences of contexts is sampled i.i.d. from a distribution over sequences of contexts, $\mathcal{W}$ i.e., $\{C_{i:1:T}\}_{i=1}^M \sim \mathcal{W}^M$ and $S_{i:1:T}, Q_{i:1:T} \sim C_{i:1:T}$. Next, the continual learning algorithm, CL, can be learned using the gradient $\nabla_\phi \sum_{i=1}^M \mathcal{L}(CL_\phi(S_{i:1:T}), Q_{i:t})$, for $i < N < M$ and evaluated on the remaining sets $\sum_{i=N}^M \sum_{t=1}^T \mathcal{L}(CL_\phi(S_{1:i:T}), Q_{i:t})$.

Continual-meta learning considers a sequence of datasets $S_{1:T}, Q_{1:T}$ as $C_{1:T}$. At training (continual learning) time, $S_{1:T}$ is both used as a support and query set: $S_t$ is used as the query set and $S_{t-1}$ as the support. Predictions at time $t$ are made using $f_\theta_t = A_\phi(Q_{t-1})$. In other words, local stationarity is assumed and the model always fails on its first prediction when the task switches. Next, using $l_t = \mathcal{L}(f_\theta_t, S_t)$, the learning of $\phi$ is performed using gradient descent of $\nabla_\phi l_t$. The evaluation is performed at the end of the sequence where $A_\phi$ recomputes fast weights using the previous supports and is tested on the query set, i.e., $\sum_{t=1}^T \mathcal{L}(A_\phi(S_t), Q_t)$.

#### 3.3. Proposed setting

Current continual learning scenarios focus on incremental task learning (Kirkpatrick et al., 2017; Javed & White, 2019; Aljundi et al., 2019a), where methods should learn not to forget already acquired knowledge. However, forcing models
Table 1. A unifying framework to explain the space of different machine learning settings. Data sampling, fast weights computation and slow weights updates as well as evaluation protocol are presented with meta-learning terminology, i.e., the support set $S$ and query set $Q$. to retain their performance on all previously seen tasks can be an unrealistic constraint, particularly with limited computational resources (Kaelbling, 1991; 1993). Relaxing this constraint can enable faster and more efficient adaptation. For instance, partially forgetting a task that appears rarely allows for re-allocation of modeling capacity to learning tasks that are encountered more frequently. Further, previous settings focus on optimizing the final performance on all tasks. An application deployed in the real world may be evaluated by its real-time decision-making performance (Kaelbling, 1991; 1993).

We thus propose OSAKA, a new approach to continual learning which lifts some of the limitations of current ones. The proposed setting is aligned with the use case of deploying a pre-trained agent, embedded or not, in the real world where it faces new or unexpected situations. The agent must adapt quickly to changes and learn new concepts if needed. OSAKA is characterized by the following properties.

**Task agnostic.** Most previous continual-learning works assume $\mathcal{C}$ to be available for training (Kirkpatrick et al., 2017; Nguyen et al., 2018; Lopez-Paz & Ranzato, 2017), which is unrealistic in many real applications, e.g., an embedded agent in a changing environment or any time series forecasting system. Thus, task-agnostic (or task-free) CL has been motivated and studied in recent works (Aljundi et al., 2019b; Zeno et al., 2018; He et al., 2019; Lesort et al., 2019b). Likewise, in OSAKA, the task boundaries are unobserved, and the agent must infer the current task or context $\mathcal{C}_t$.

**Pre-training.** In most settings (Kirkpatrick et al., 2017; He et al., 2019), the agent begins learning from a randomly-initialized set of parameters. This practice is not aligned with real-life CL scenarios since it is unrealistic to deploy an agent without any knowledge about the world (Lesort et al., 2019b; Lomonaco et al., 2019b). Furthermore, real-life non-i.i.d. training is difficult. Accordingly, OSAKA allows pre-training of any kind, e.g., i.i.d. training. We refer to this phase as pre-training time, and the deployment phase as continual-learning time.

**Out-of-distribution tasks.** Current settings learn tasks sampled from a single dataset (Javed & White, 2019; He et al., 2019) that have to be remembered at continual-learning time. However, OSAKA is a more challenging setting where the model has to learn new tasks online, even when those tasks are sampled from new distributions not encountered at pre-training. This setting is more realistic than previous ones since an agent will most surely encounter unexpected situations in real life requiring the algorithm to update its representations by, e.g., learning new discriminative features or new policies. For instance, this behavior could arise when an embedded agent learns to manipulate a new object or tool, or a virtual teacher learns a new concept.

**Task revisiting.** Standard CL focuses on methods for incrementally learning strictly new tasks. However, most CL applications will operate in a setting where they will revisit tasks or parts of their environment or domain. Accordingly, we assume that $\{\mathcal{C}_t\}_{t=1}^T$ follow a Markov chain with transition probabilities $P(\mathcal{C}_t | \mathcal{C}_{t-1})$. This is known task revisiting as recurrent concept drift (Gama et al., 2014). This assumption brings us closer to real applications such as reinforcement learning where the states follow a Markov chain given the previous state and action (Kaelbling et al., 1996). Further, OSAKA allows switching $\mathcal{C}_t$ back and forth from old tasks to OoD tasks. This provides a more challenging setting where models have to infer when the task changes and whether the current task is a new (OoD) task or an old one.

**Controllable non-stationarity.** The non-stationarity level of standard CL is often provided through the dataset sizes and the number of classes per task. Past works then design algorithms tailored to these levels of non-stationarity. Furthermore, real-life applications often operate on locally stationary data distributions, e.g., an autonomous vehicle navigating specific weather, a recommendation system dealing with users with time-varying interest (Hidasi et al., 2015), or an embedded agent doing a specific task for a
We propose Continual-MAML (see Fig. 1), a continual learning (CL) baseline based on MAML (Finn et al., 2017) that can cope with the challenges of OSAKA. Continual-MAML (Algorithm 1) consists of two stages: pre-training and continual learning.

The pre-training phase consists of MAML, i.e., meta-learning model parameters such that a small number of gradient steps with a small amount of training data from a new task will produce good generalization performance on that task (Algorithm 1, lines 5–12). Specifically, the model adapts its initial weights to multiple tasks in the inner loop (Algorithm 1, lines 7–10) and updates the initialization in the outer loop (Algorithm 1, line 11). Note that the inner loop learning rate is meta-learned ($\phi_\eta$ in Algorithm 1, line 9).

At CL time (Algorithm 1, lines 14–24), the inner loop optimization adapts the model to the current task. Specifically, the model uses current data $X_t, Y_t$ to obtain fast weights (Algorithm 1, line 18). Assuming that the data is locally stationary, it makes a prediction on the following data $X_{t+1}$ and incurs a loss (Algorithm 1, line 17). The model will fail at its first prediction because its fast weights $\theta$ are not suited for the new task yet, but it will have recovered by the next. The recovery is achieved by learning new fast weights $\theta$ once the algorithm gets feedback on its prediction (Algorithm 1, line 18). Note that for some real-life applications, this feedback could be delayed (Kaelbling et al., 1996). Furthermore, the algorithm must update its knowledge only when it is solving an OoD task. Accordingly, when $\mathcal{L}(f_{\theta_{t-1}}(X_t), Y_t) > \epsilon$, new knowledge is incorporated through outer loop optimization of the learned initialization. As a result, different from previous CL literature, the proposed algorithm benefits from fast adaptation, dynamic representations, task boundary detection, and computational efficiency, as we describe next.

**Fast Adaption** During pre-training, Continual-MAML learns a weight initialization that adapts fast to new tasks. This is different from CL methods that focus on incorporating as much knowledge as possible into one representation that has to maximize performance in a multi-task regime.

**Dynamic representations** In OSAKA, significant distribution shifts occur periodically. Thus, as shown in Section 5, models that require a fixed representation would fail to adapt. Instead, Continual-MAML incorporates a mechanism to detect distribution shifts and to learn new knowledge using outer-loop optimization (see Algorithm 1, lines 21–23).

**Task boundary detection** Continual-MAML also monitors the difference in loss with respect to the previous task in order to avoid mixing gradient information from two different distributions (Algorithm 1, line 19). We refer to this mechanism, and the previous one (Algorithm 1 lines 19-23) as *knowing what to train on* (KWTO).

**Computational efficiency** As described by Farquhar & Gal (2018), CL agents should operate under restricted com-
putational resources since remembering becomes trivial in the infinite-resource setting. Continual-MAML satisfies this desideratum by allowing the agent to forget (to some extent) and re-allocate parametric capacity to new tasks. Likewise, no computationally expensive mechanisms, such as replay (Chaudhry et al., 2019), or BGD (Zeno et al., 2018; He et al., 2019), is used to alleviate catastrophic forgetting in our method.

### Algorithm 1: Continual-MAML

| Line | Description |
|------|-------------|
| 1    | **Require:** $P(T_{\text{pre}}), P(T_{\text{cl}})$: distributions of tasks |
| 2    | **Require:** $\gamma, \epsilon$: threshold hyperparameters |
| 3    | **Require:** $\eta$: step size hyperparameter |
| 4    | **Initialize:** $\phi, \theta$: Meta and fast adaptation params |
| 5    | **while pre-training** do |
| 6    | Sample batch of tasks $\{T_i\}_{i=1}^{B} \sim P(T_{\text{pre}})$ |
| 7    | **foreach** $T_i$ do |
| 8    | Sample data from task $X_i, Y_i \sim P(T_i)$ |
| 9    | $\theta_i \leftarrow \phi - \phi \eta \nabla_{\phi} \mathcal{L}(f_{\theta_i}(X_i[:]), Y_i[:])$ |
| 10   | end |
| 11   | $\phi \leftarrow \phi - \eta \nabla_{\phi} \sum_i \mathcal{L}(f_{\theta_i}(X_i[:]), Y_i[:])$ |
| 12   | **end** |
| 13   | **Initialize:** current parameters $\theta_0 \leftarrow \phi$ |
| 14   | **while continually learning** do |
| 15   | Sample current task $T_i \sim P(T_{\text{cl}}|T_{i-1})$ |
| 16   | Sample data from task $X_i, Y_i \sim P(T_i)$ |
| 17   | Incur loss $\mathcal{L}(f_{\theta_{i-1}}(X_i), Y_i)$ |
| 18   | $\theta_i \leftarrow \phi - \phi \eta \nabla_{\phi} \mathcal{L}(f_{\theta_i}(X_i), Y_i)$ |
| 19   | if $\mathcal{L}(f_{\theta_{i-1}}(X_i), Y_i) - \mathcal{L}(f_{\theta_i}(X_i), Y_i) < \gamma$ then |
| 20   | No task boundary detected |
| 21   | if $\mathcal{L}(f_{\theta_{i-1}}(X_i), Y_i) > \epsilon$ then |
| 22   | Adding Knowledge |
| 23   | $\phi \leftarrow \phi - \eta \nabla_{\phi} \mathcal{L}(f_{\theta_{i-1}}(X_i), Y_i)$ |
| 24   | $\phi \leftarrow \phi - \eta \nabla_{\phi} \mathcal{L}(f_{\theta_{i}}(X_i), Y_i)$ |
| 25   | $i \leftarrow i + 1$ |

5. Experiments

We study the performance of different baselines in the proposed OSAKA setup. We first introduce the datasets, methods, and baselines, and then the experimental results.

5.1. Datasets

For all datasets (See Figure 5.1), we study two different levels of non-stationarity at CL time, $\alpha$ values of 0.98 and 0.90. We adapt other hyperparameters (support size, number of classes per task, and the total number of predictions) according to each dataset’s size and difficulty.

**Omniglot / MNIST / FashionMNIST** In this setup, models are pre-trained on the first 1,000 classes of Omniglot (Lake et al., 2015). At CL time, the model is exposed to the full Omniglot dataset, and to two out-of-distribution datasets: MNIST (LeCun & Cortes, 2010) and FashionMNIST (Xiao et al., 2017). With respect to reported performance, MNIST is a simpler dataset than Omniglot, and FashionMNIST is the hardest. During CL time, the task switches with a probability $1 - \alpha$. When switching, the probability of switching to Omniglot, MNIST, or FashionMNIST is 0.5, 0.25, and 0.25, respectively. For this dataset, we sample 10-way 1-shot classification tasks. CL episodes correspond to 50,000 online predictions or timesteps.

**Symbols** In this setup, the models are pre-trained to classify characters from different alphabets on randomized backgrounds (Lacoste et al., 2018). Tasks consist of 4 different symbols with four examples per symbol. At continual-learning time, the model is exposed to a new alphabet. Furthermore, the model will have to solve the OoD task of font classification, where the input distribution does not change, only its mapping to the output space. The font classification task consists of 4 different fonts with 4 symbols per font. All three tasks switch with equal probability $p = 0.33$. CL episodes correspond to 10,000 timesteps.

**Tiered-ImageNet** Like Omniglot, Tiered-ImageNet (Ren et al., 2018) groups classes into super-categories corresponding to higher-level nodes in the ImageNet (Deng et al., 2009) hierarchy (20, 6, and 8 disjoint sets of training, validation, and testing nodes). We use these higher-level splits in order to simulate a shift of distribution. Thus, at pre-training time, the model is presented with 14 high-level categories from the original training split. At CL time, we use six new super-categories from the original validation split, as well as the
remaining six categories from training. The probabilities for visiting the two subsets from the training split and the validation split are equally 0.33. CL episodes correspond to 10,000 timesteps.

5.2. Baselines

Table 2 compares the main features of each baseline that we benchmark in the OSAKAs setting. For meta-learning methods, ADAM (Kingma & Ba, 2014) and SGD are used for the outer and inner updates, respectively.

Online ADAM. As a lower bound, we use ADAM without pre-training.

Fine tuning. To study the effect of pre-training, we pre-train the model and fine tune it at CL time.

BGD (Zeno et al., 2018). Bayesian Gradient Descent (BGD) is a continual learning algorithm that models the distribution of the parameter vector $\phi$ with a factorized Gaussian. Similarly to (He et al., 2019) we apply BGD during the continual learning phase. More details about this baseline are provided in Appendix C.

MAML (Finn et al., 2017). MAML consists of a pre-training stage and a fine-tuning stage. During pre-training, the model learns a general representation that is common between the tasks. In the fine-tuning stage, the model fine-tunes its layers to adapt to a new task.

ANIL (Raghu et al., 2019). ANIL differs from MAML only in the fine-tuning stage. Instead of adapting all the network layers, ANIL adapts only the network head towards the new task. The goal of this baseline is to show the problem with static representations in the continual learning setup. ANIL is representative of meta-continual learning.

MetaBGD and MetaCOG (He et al., 2019). MetaBGD performs continual-meta learning using MAML and BGD to alleviate catastrophic forgetting. MetaCOG introduces a per-parameter mask learned in the inner loop.

5.3. Experimental results

| MODEL          | PRE-TRAIN | RETRAIN |
|----------------|-----------|---------|
|                | MAML      | ANIL    | MAML | SGD | BGD | KWTO |
| ONLINE ADAM    | x         | x       | x    |    |     | x    |
| FINE TUNING    | x         |         | x    |     |     | x    |
| BGD (Zeno et al., 2018) | x         | x       | x    |     |     | x    |
| MAML (Finn et al., 2017) | x         | x       | x    | x  |     | N/A  |
| ANIL (Raghu et al., 2019) | x         | x       | x    | x  |     | N/A  |
| MetaBGD (He et al., 2019) | x         | x       | x    |     |     | x    |
| MetaCOG (He et al., 2019) | x         | x       | x    |     |     | x    |
| CONTINUAL-MAML | x         | x       | x    |     |     | x    |

Table 2. Baseline comparison. Columns 2–3 contain pre-training algorithms. Columns 4–7 show training algorithms at continual learning time. KWTO is out knowing what to train on method.

For all benchmarks, we report results on two $\alpha$-locally-stationary environments in Table 3 for Omniglot/MNIST, FashionMNIST, Table 4 for symbols, and Table 5 for Tiered-ImageNet.

We found that algorithms perform better when local stationarity is strongly enforced ($\alpha \geq 0.98$) because they spend more time in each context/task before switching. We found that the most critical model feature in this setup is fast adaptation (or meta learning), as highlighted by the performance gap between Online ADAM and Continual-MAML (up to +29%). This gain comes from two advantages: quickly changing weights after a task/context switch, having slow ($\phi$), and fast ($\theta$) weights, which alleviate catastrophic forgetting. Next, to correctly classify the OoD data (e.g. symbols font task), models need the ability to adapt their embedded space. For instance, the dynamic representations of Continual-MAML offer a 49% and a 35% improvement on MNIST and FashionMNIST compared to MAML and ANIL. This result demonstrates the inapplicability of MCL to real scenarios. Although MCL can continually learn new tasks without forgetting, its static embedded space will prevent it from learning tasks lying outside of the pre-training data distribution. Moreover, adding BGD to slow-down forgetting prevents the model from acquiring new knowledge. Removing this feature, e.g. from MetaBGD to Continual-MAML, increases the performance up to 12.2% while requiring less computation. Lastly, the task boundary detection method (KWTO) removes unnecessary retraining on in-distribution tasks and thus reduces forgetting. KWTO improves Continual-MAML accuracy by up to 7%.

With more frequent switches of distribution ($\alpha \geq 0.90$), methods without meta learning suffered from more performance degradation than in the previous setting ($\alpha \geq 0.98$). In fact, in this setting, multiple models collapsed to a random predictor (Online ADAM, Fine Tuning, BGD, and MetaCOG). On the other hand, most meta-learning methods suffered from smaller degradation in performance, validating our hypothesis that fast adaptation is a crucial feature for handling rapidly changing data distributions.

When focusing on each particular benchmark, pre-training did not improve Continual-MAML for Omniglot/MNIST/FashionMNIST, as the datasets could be learned rapidly. In the symbols benchmark, the font classification task highlights that learning a new mapping from the same inputs to a new output space is challenging when the embedded space is static. Comparing MAML and ANIL with Continual-MAML + pre-train, we observe that dynamic representations almost doubled the accuracy. In the Tiered-ImageNet benchmark, all tasks are more similar to each other than in Omniglot/MNIST/FashionMNIST or symbols. This setup is more similar to the setups used in He et al. (2019); Raghu et al. (2019); Finn et al. (2017). Thus,
for $\alpha = 0.9$, we found that ANIL was better suited for this task overall, although Continual-MAML was able to yield better performance in the OoD case.

### 6. Conclusions

We propose OSAKA a new approach to continual learning that focuses on online adaptation and fast remembering. This framework is task agnostic, allows pre-training, and introduces OoD tasks at continual-learning time. Furthermore, tasks can be revisited, and different levels of non-stationarity can be tested. We argue that OSAKAs is better aligned with real-life applications of continual learning.

We show that the proposed setting is challenging for current methods in the literature that were designed for other scenarios. We introduce Continual-MAML, an initial baseline that addresses the challenges of OSAKA. Continual-MAML pre-trains a representation that adapts fast to new tasks at continual-learning time. In order to cope with the challenges of OSAKA, Continual-MAML detects sudden shifts of the task distribution to incorporate new knowledge to the pre-trained representation. In extensive experiments on Omniglot, MNIST, FashionMNIST, tiered-ImageNet, and symbols we show that Continual-MAML is better suited to OSAKA than standard continual learning and meta learning methods, as well as meta-continual learning and continual-meta learning.

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A. Experimental Details

The procedure followed to perform the experiments in Section 5 is described next in detail.

A.1. Implementation details

For all experiments, we used a 4-layer convolutional neural network with 64 hidden units as commonly used in the few-shot literature (Vinyals et al., 2016; Snell et al., 2017; Sung et al., 2018). All the methods were implemented using the PyTorch library (Paszke et al., 2019), and run on a single 12GB GPU. Hyperparameters were found by random search. During hyperparameter search, we allocated the same amount of computation for each method and baseline with some exceptions. All methods using BGD, i.e., BGD, MetaBGD and MetaCOG, were allocated ten times more computation because of their extra overhead due to regularization. The search space is shown in Table 6. We used Adam (Kingma & Ba, 2014) for the outer-loop optimization.

B. Categorization of related works

In Table 7, we position our method with respect to other continual learning settings.

C. Bayesian Gradient Descent

Bayesian Gradient Descent (BGD) is a continual learning algorithm that models the distribution of the parameter vector $\phi$ by a factorized Gaussian. Similarly to (He et al., 2019) we apply BGD during the continual learning phase. BGD models the distribution of the parameter vector $\phi$ by a factorized Gaussian $q(\phi) = \prod_i \mathcal{N}(\phi_i | \mu_i, \sigma_i^2)$. Essential motivation behind BGD is that $\sigma$ models the uncertainty of the estimation of the parameter $\phi$. Hence parameters with higher uncertainty should be allowed to change faster than the parameters with lower $\sigma$, which are more important for preserving knowledge learned so far. BGD leverages variational Bayes techniques (Graves, 2011) and introduces an explicit closed-form update rule for the parameters $\mu_i$ and $\sigma_i$:

$$
\mu_i = \mu_i - \eta \sigma^2 \mathbb{E}_i \left( \frac{\partial \mathcal{L}(f_{\theta_{t-1}}(X_t), Y_t)}{\partial \phi} \right),
$$

$$
\sigma_i = \sigma_i \sqrt{1 + \left( \frac{1}{2} \mathbb{E}_i \left[ \frac{\partial \mathcal{L}(f_{\theta_{t-1}}(X_t), Y_t)}{\partial \phi} \right] \right) - \frac{1}{2} \mathbb{E}_i \left[ \frac{\partial \mathcal{L}(f_{\theta_{t-1}}(X_t), Y_t)}{\partial \phi} \right] \epsilon_i},
$$

where the expectations are approximated using Monte Carlo sampling and the re-parametrization trick is used as $\phi_i = \mu_i + \sigma_i \epsilon_i, \epsilon_i \sim \mathcal{N}(0, 1)$.

| Outer step size | 1 L-1 | 2 | 3 | 4 | 5 |
|----------------|------|---|---|---|---|
| Inner step size | 10-1 | $5 \cdot 10^{-2}$ | 10-2 | - | - |
| Inner iters    | 1 | 2 | 4 | 8 | 16 |
| Batch size     | 2 | 4 | 8 | 16 | 25 |

*Table 6. Hyperparameter search space.*
Table 7. **Related Work.** We compare OSAKA with other settings in terms of the final objective, environment, and features of the continual learning method. The last column categorizes the different baselines used in this work.