Continual Feature Selection: Spurious Features in Continual Learning

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Abstract

Continual Learning (CL) is the research field addressing learning settings where the data distribution is not static. This paper studies spurious features’ influence on continual learning algorithms. Indeed, we show that learning algorithms solve tasks by overfitting features that are not generalizable. To better understand these phenomena and their impact, we propose a domain incremental scenario that we study through various out-of-distribution generalizations and continual learning algorithms. The experiments of this paper show that continual learning algorithms face two related challenges: (1) the spurious features challenge: some features are well correlated with labels in train data but not in test data due to a covariate shift between train and test. (2) the local spurious features challenge: some features correlate well with labels within a task but not within the whole task sequence. The challenge is to learn general features that are neither spurious (in general) nor locally spurious. We prove that the latter is a major cause of performance decrease in continual learning along with catastrophic forgetting. Our results indicate that the best solution to overcome the feature selection problems varies depending on the correlation between spurious features (SFs) and labels. The vanilla replay approach seems to be a powerful approach to deal with SFs, which could explain its good performance in the continual learning literature. This paper presents a different way of understanding performance decrease in continual learning by describing the influence of spurious/local spurious features.

1 Introduction

![Illustration of spurious features and local spurious features.](image)

If the task is to distinguish the squares from the circles. In figures (a) and (b), we can see that the color is a spurious feature. The colors in the training data are different than the color in the test data: there is a covariate shift between train and test. In figures (c) and (d), the colors are virtually spurious in task 1. The colors also exist in test, but they are not discriminative while they appear to be discriminative in task 1.

Feature selection is a classical machine learning problem. Its objective is three-fold: “improving the prediction performance of the predictors, providing faster and more cost-effective predictors, and providing a better understanding of the underlying process that generated the data” [12]. In this paper, we are interested in improving prediction performance. In the independently and identically distributed (iid) setting (non-continual), algorithms’ performance is intrinsically dependent on the feature distribution. A bad distribution of features, e.g. with a covariate shift between train and test data, will lead to bad performance. The problem of spurious feature arises when the covariate shift is characterized by a feature that correlates well with training labels but not with test labels: a spurious feature. In this case, the learning algorithm can trivially solve train data but fails to generalize to test data.

In continual learning, algorithms are trained from a data distribution that changes through time. Hence, we could expect that spurious features (SFs) in one state of the data distribution will not last in the next state. Hence, if a continual learning algorithm uses a SF to solve a task, it could be resilient and learn better features given more data. For example, algorithms could aim to detect and fix spurious representation learned in the past [14]. An example of
a task with spurious features could be a classification task between cars and bikes, but in the training data, all cars are red, and all bikes are white. A model could easily overfit the color feature to solve the task. This problem is notably caused by a covariate shift between train data and test data. In continual learning, we expect that future tasks will bring pictures of different cars and bikes that will allow the model to learn better representations.

Moreover, in continual learning, a second type of spurious features can be described: local spurious features. Local features denote features contributing to solving a task (at least a subset of the whole scenario). They can either be generalizable within the whole sequence of tasks or not. If not, they become unnecessary or bad when new data arrives: we denote them local spurious features. They correlate well with labels within a task but not within the full task sequence. This problem is provoked by the unavailability of all data and is not provoked by a covariate shift. It is, therefore, a problem that is specific to continual learning settings.

In this paper, we investigate both the problem of spurious features (with covariate shift) and local spurious features (without covariate shift).

Here are the contributions of this paper:

- We propose a methodology to highlight the problems of spurious features and local spurious features in continual learning.
- We describe the implications of those problems in various continual learning settings and approaches.
- We propose a binary CIFAR10 scenario SpuriousCIFAR2 inspired from colored MNIST to experiment with trivial spurious correlations.
- We experiment with various algorithms from the Out-of-Distribution (OOD) generalization and from continual learning bibliography.
- We identify local spurious features as a core challenge for continual learning algorithms along catastrophic forgetting.

We expect this paper to be a first step in investigating how spurious features and spurious local features critically contribute to performance decrease in continual learning.

2 Problem Formulation

This section introduces how continual learning deals with features in a single task and in a sequence of tasks. The goal is to present the key concepts for continual feature selection. The main problem to solve is How to learn general features from only a subset of the data? First, we will disentangle and describe general features, local features, and spurious features. Secondly, we will present the different conditions making continual learning with spurious features more or less harder.

2.1 General, Local, Spurious and Local Spurious Features

General Formalism

We consider a continual scenario of classification tasks. We study a function \( f_\theta(\cdot) \), implemented as a neural network, parameterized by a vector of parameters \( \theta \in \mathbb{R}^p \) (where \( p \) is the number of parameters) representing the set of weight matrices and bias vectors of a deep network. In continual learning, the goal is to find a solution \( \theta^* \) by minimizing a loss \( L \) on a stream of data formalized as a sequence of tasks \([T_0, T_1, \ldots, T_{T-1}]\), such that

\[
\forall (x_t, y_t) \sim T_t (t \in [0, T - 1]), f_{\theta^*}(x_t) = y_t.
\]

Let \( Z \) be a feature in the input data, and \( g(\cdot) \) a function that for a class \( y \) and a dataset \( D \), \( g(D, Z, y) \) return the probability of \( Z \) being in data in \( D \) of class \( y \).

More formally, we can define \( g(D, Z, y) \) as:

\[
g(D, Z, y) = \frac{1}{N_y} \sum_{x \sim D_y} w(x, Z)
\]
With $\mathcal{D}_y$ the subset of $\mathcal{D}$ with $y$ as label, $N_y = Card(\mathcal{D}_y)$ and $w(.)$ a function which return 1 if $Z$ is in $x$ and 0 if not. $w(.)$ is binary as a sake of simplicity.

We can then define a discriminative feature as an hypothesis. $Z$ is discriminative for class $y$ in $\mathcal{D}$ if:

$$\forall y' \in Y \quad g(\mathcal{D}, Z, y) >> g(\mathcal{D}, Z, y') \quad (2)$$

Then a good features $Z_t$, for a class $y$, respect (2) for training data $\mathcal{D}_t$, and test data $\mathcal{D}_{te}$.

A spurious feature $Z_{spur}$ for a class $y$ respect (2) for training data $\mathcal{D}_t$, but not for test data $\mathcal{D}_{te}$. A spurious feature is well correlated with labels in training data but not with testing data.

**Global vs Local Solution**

While learning on a task $t$, we can distinguish a local solution $\theta^*_t$, satisfying for the current task $T_t$, from a global solution $\theta^*_T$ that is satisfying for all tasks $C_T$ (past, current, and future), i.e. for the whole scenario.

Similarly, we can differentiate local and global features, contributing to local and global solutions. The global features are the good features $Z_+$ that are useful for the solution of the scenario. Unfortunately, at time $t$, we can not know if a feature is part of $Z_+$ without access to the future. Therefore, algorithms should learn given their current data but update their knowledge afterward given new data.

For example, in classification, the discriminative features for a given class depend on all the classes. Therefore, discriminative features can become outdated in class-incremental scenarios when new classes arrive.

At time $t$, we can define local features $Z_t$ for a class $y_t$ in a task $T_t$ as a feature that respect (2) for $g(T_t, Z_t, y_t)$.

**Spurious Features and Local Spurious Features**

As described earlier, spurious features, $Z_{spur}$, are features that correlate well with training labels but not with testing labels. In contrast, the global features $Z_+$ correlate well with training and testing data. Hence, learning from $Z_{spur}$ may offer a low training error but high test error. Without additional information, if the $Z_{spur}$ are more correlated to labels than $Z_+$, it is impossible to distinguish them while learning. $Z_{spur}$ are due to a covariate shift between train and test distribution.

In continual learning, the covariate shift between train and test $Z_{spur}$ may also lead to poor generalization. On the other hand, the features can be locally spurious, i.e., they locally correlate well with labels within a task but not within the whole scenario. We name them local spurious features. We illustrate the difference between spurious features and local spurious features in Figure[1]

At task $t$, a local spurious feature $Z_{spur,t}$ respect (2) for a class $y_t$ in task $T_t$, but not for the whole scenario $C_T$. In other words, $Z_{spur,t}$ correlate well with labels on the current task but not with the whole scenario. $Z_{spur,t}$ can be extended from a single task $T_t$ to all tasks seen so far $T_{0:t}$ without loss of generality.

### 2.2 Opportunities and Challenges

The data distribution being not static in continual learning, we can expect that spurious feature $Z_{spur}$ are only present in a state of the data distribution, e.g., only during one task. Continual learning algorithm should then be able to detect features that are not constantly present and ignore them as in [14].

On the other hand, the particularity of continual learning bring a new challenge to deal with: local spurious features. Hence, not spurious features when all data are available may become spurious if only a subset of the data is available.

In this paper, we will experiment with how to deal with spurious features and highlight the problems that local spurious features might bring.

### 2.3 Spurious Correlations: Different cases

We can identify different cases among the spurious correlation between features and labels.

**Data Observability:**

- fully observable data [14], all good features are always observable. In this case, we can assume that features in data that do not last are spurious, and we can learn to ignore them.

- partially observable data, all good features are not always observable. In this case, features that do not last can either be spurious or good.

We can parallel with the difference between MDP (Markov Decision Process) and POMDP (Partially Observable Markov Decision Process) in reinforcement settings.

**Noise of Spurious Features:**

- SFs are Noise, in this case, we can just assume that features in data that do not last are spurious and we can learn to ignore them.
SFs are true features for other classes e.g., for classification, the color can be a spurious feature for some classes and valuable for others. We cannot ignore those features since it would lead to poor performance in other classes.

Unfortunately, the characteristics of spurious features (SFs) can make a learning scenario unsolvable, the hardest settings being when data are only partially observable, and the SFs are true features. The question raises then on “what are the limits between a solvable data setting and an unsolvable one?” This paper empirically investigates some of those limits with current algorithms on the degree of correlation between the SFs and the labels, and the amount of support data in each task.

In our experiment, we create one setting with both fully observable and partially observable data. Our spurious features are noise in our domain incremental experiments and true features in our class-incremental experiments. But we do not exploit information about spurious feature types to design approaches.

3 Consequences in CL Settings

In continual learning, two basic types of benchmarks are usually studied (1) Class-Incremental - new data brings new classes -, and Domain Incremental - new data are from already known classes but can be from another domain of the data distribution - [16, 20]. In the presence of spurious features with covariate shift, the spurious features are in the training and the validation data of each task but are not in the final test set.

3.1 Class-Incremental

Class-Incremental settings are designed to evaluate the capacity of models to learn incrementally to classify classes. By definition and for evaluation purposes, classes are seen in only one task and never again. This is a good way to evaluate the capacity to learn, retain information, and avoid catastrophic forgetting. Still, it does not make it possible to reevaluate past knowledge with new data [5].

The only way to improve the representation of past tasks/classes is then to do replay to confront past data with new data [13]. In this setting, learning on the data of one class should lead to learning representations that are good for in-distribution data (past and current classes) and out-of-distribution data (future classes). The future data being unavailable, it is highly probable that some of the learned features locally are not global discriminative features, therefore, are local spurious features. Hence, the risk of spurious features is not negligible in class-incremental scenarios.

We can note that catastrophic forgetting is often assimilated to important weights modification [8, 6]; however, spurious correlation (and even local features) can also decrease performance without modifying important weights. Models that need to learn new representation to understand past tasks better are forced to operate a representation drift [4] (also called projection drift [17]) to maximize final accuracy.

Hence, this setting could be used to analyze local vs. global vs. spurious features. However, there is a risk that catastrophic forgetting interferes with bad features and entangle results. We propose first using domain incremental setting, where catastrophic forgetting is generally less intense, to simplify the problem and better highlight spurious features’ troubles. In a second time, we will use a Class-Incremental scenario to highlights local spurious features challenges.

3.2 Domain Incremental

Domain incremental settings are scenarios where the classes stay the same, but the data distribution changes. This setting is a way to evaluate how models can improve their knowledge/understanding of a concept or a class. The goal of the models is to find invariant features from several domains to predict accurately on all domains, it can also accumulate features that are complementary to characterize a class but that are not necessarily invariant.

In continual learning, famous domain incremental settings are permutMNIST and rotated MNIST. Still, recent research in out of distribution generalization proposes interesting benchmarks that can be adapted into a domain incremental setting, such as in DomainBed datasets [10].

In this paper, we would like to study how approaches can deal with spurious correlation in a continual learning setting. Ideally, even if the model can not perfectly learn with spurious features in the first task, we would like that after seeing many domains (or environments), the model learns how to ignore spurious features and find invariant features if possible.

This paper will experiment mainly with domain incremental since this setting is easier and compatible with most approaches. Moreover, we also experiment with simple class-incremental experiments to show that spurious local features have a significant impact in this setting.
Figure 2: Data generation model of SpuriousCIFAR2 scenario. The good features $Z_+$ are generated from the labels and $Z_{spu}$ are generated from the task label.

4 Related Works

In large part of the continual learning bibliography, algorithms assume that to avoid catastrophic forgetting, they should not increase the loss on past tasks [15, 25]. It leads to the definition of interference/forgetting of [24]:

$$\text{Interference} : \frac{\partial L(x_i, y_i)}{\partial \theta} \cdot \frac{\partial L(x_j, y_j)}{\partial \theta} < 0$$ (3)

$\forall (x_i, y_i) \in T_i$ and $\forall (x_j, y_j) \in T_j$ with $j > i$, · the dot product operator. Following, this definition increasing the loss on past tasks necessarily leads to forgetting.

However, in the presence of spurious features, the algorithm might have learned spurious/local features that need to be replaced by good features. It means that the loss needs to be temporarily increased to reach a more general solution.

Then, the presence of spurious features is adversarial to most continual regularization strategies. Indeed, if we measure weights importance or example with fisher information, high importance will be given to weights using spurious features. Moreover, interference or transfer (eq. 3) as define in [24] are not applicable.

The memorization of continual learning algorithm should be adapted to spurious features. Strategies like regularization, dynamic architectures [21] freeze weights or synthesize data such as pseudo-rehearsal (e.g. dataset distillation [28]). They are prone to memorize spurious features or local spurious features while ignoring meaningful information. Moreover without replay, those approaches can not fix bad representations afterwards.

Vanilla rehearsal or generative replay can be a good solution to avoid forgetting meaningful information. Replay methods have been shown in the bibliography to be efficient and versatile even in their most straightforward form [23]. Notably, all current state-of-the-art approach on ImageNet use replay [7, 29]. Replay is also the mechanism that enables meta-continual learning [13, 11, 27], namely when algorithms learn how to learn without forgetting, to work in practice.

The research field that usually deals with spurious correlation is the out-of-distribution (OOD) generalization field. It received a lot of attention in recent years, especially since the IRM (Invariant Risk Minimization) [2] paper. OOD approaches target training scenarios where there are several training environments within which different spurious features correlate with labels. The goal then is to learn invariant features among all environments to build an invariant predictor in all training environments and potentially any other [2, 1] [26, 22].

5 Spurious Features

In the first experimental section of this paper, we would like to estimate if continual learning algorithms can deal with spurious features. We design a scenario with spurious features that change at each task. We create various scenarios with various correlations between spurious features and labels and train various baselines to assess continual learning capabilities. We also vary the amount of data in each task and test potential solutions for spurious features.

5.1 Setting

We propose a benchmark similar to colored MNIST [2] with CIFAR10. We convert the ten ways classification dataset into a binary dataset. The new classes are “transportation means versus not a transportation means”, i.e. cars, trucks, ship, airplane, and horse versus the other classes: birds, cats, dogs, deers, frogs. The goal is to have a simple setting more challenging than colored MNIST with true features that are built upon all three color channels.

The spurious feature is a square of color. We sample two colors randomly (one per class) and add a $2 \times 2$ pixels square of that color randomly positioned in the images (example Fig. 3a). We can vary the percentage of images
with the spurious feature to reduce or grow the correlation between the spurious feature and the labels. A correlation of 1 means that all images have a colored square.

The scenario is then a sequence of SpuriousCIFAR2 datasets with different colors of spurious features. We illustrate two environments and the test set in Figure 3 and the data generation process in Fig. 2. The good features are invariant through tasks if each task contains the full dataset. However, the scenario can be made harder by only keeping a subset of the dataset in each task, and then the good features are not invariant in the training data.

The test set of the environment is the binarized version of CIFAR10 test set without any spurious features.

**Setting Goal:** This setting highlights how spurious features can disrupt continual learning algorithms. Moreover, it evaluates the capacity of algorithms to question and modify their past knowledge to improve test accuracy. This setting is made for algorithms training under the assumption that for a given input data $x$, the conditional distribution $p(y|x)$ is invariant, i.e. there is no real concept drift [16].

The experimentation aims to highlight and discuss the problems that spurious correlation can bring to existing approaches. The setting being very simple, it would be quite easy to propose a ad-hoc solution to ignore the, here easily detectable, spurious features without fundamentally solving any problem.

Hence, in the next section, we experiment with a continual learning approach and adapt some OOD approaches to continual learning. This adaptation is made by simply adding a replay process to an OOD approach; hence, we simulate a multi-environment at each task by replaying a subset of past tasks.

### 5.2 Approaches

In this paper, we experiment with a vanilla replay method and simple finetuning.

The replay buffer is constructed by randomly selecting $N$ samples per class. The buffer is then sampled to keep class distribution balanced over all tasks. Balancing samples distribution over classes is made to avoid training troubles on imbalanced datasets.

Among the existing OOD approaches, we compare with a continual version of IRM [2] and the state of the art methods IB-ERM, IB-IRM [1], GroupDRO [26] and Spectral Decoupling [22]. OOD approaches are algorithms designed to be trained on multiple environments in a multi-task fashion. They propose different regularization strategies designed to ignore spurious features and learn invariant features. The invariant features are present in all environments and are assumed to be good features. The goal of the OOD approaches is to learn an invariant predictor that would ignore spurious features and rely only on invariant features. The continual version of OOD approaches simulates multiple environments by replaying data of past tasks. We choose empirically a replay buffer storing 100 samples per class for both OOD approaches and vanilla replay (cf appendix [10] for hyper-parameters selection protocol).

### 5.3 Problems Highlights

**Overfitting the spurious features:** To assess that algorithm learning the scenario proposed overfit on the spurious features, we can compare the final test accuracy (without spurious) with the validation accuracy. In Fig. 4a we see that while learning task 0, the model fits perfectly to validation data (i.e., with spurious features) and not at all the final test data (same as validation but without spurious features). The test accuracy is near 50%, which is similar to random. This figure shows that the artificial spurious features cause the expected learning behaviors. It indicates that the model completely overfits the spurious features. Moreover, in such case, estimating importance of parameters to penalize their modification is counterproductive hence a regularization approach can not be a potential solution to
address the problem. To not rely data from different states of the distribution should be compared to each other. It justifies our choice to only compare a replay strategy with OOD strategies and not experiment with regularization or dynamic architecture for continual. Replay methods have been shown in the literature to be effective and versatile. In the following experiments, we will analyze results in continual settings.

Instability:
In Fig. 4b, we assess the test accuracy at each epoch over the whole sequence of 10 tasks. This figure indicates two interesting pieces of information. First, even in the 100% spurious correlation, baseline models can learn at some point a good solution. Secondly, even when they learn a good solution, they can easily forget it. To lighten the influence of instability on the evaluation metrics, we can report the average test accuracy instead of reporting the final test accuracy. This average can be done over the test accuracy at the end of each task. In continual learning, this evaluation is revered to average accuracy and is noted $\Omega_f$, we will note the final accuracy $\Omega_f$.

Comparing CL Baselines with OOD Baselines

Still, in the 100% spurious correlation setting, we assess now how baselines from the OOD research field behave in a continual setting.

Fig. 5 show us that {ib-erm, SpectralDecoupling and GroupDRO} show some interesting improvement over rehearsal and finetuning baselines, however they stay far from a satisfying accuracy. As a reference, we manage to train a baseline to 96.73% of accuracy on the CIFAR2 dataset (without spurious features). On the other hand, {irm}
and \textit{ib-irm} perform very poorly.

As expected, the 100\% spurious correlation scenario is not solvable in a satisfying manner by any baseline. The next experiments will analyze performance in various spurious correlation settings.

5.4 Experiments

5.4.1 Influence of Spurious Correlation

In this section, we aim to answer the question “how the level of spurious correlation influence learning algorithms?”. We can expect from a stream of tasks that the 100\% spurious correlation is quite rare. Hence, we will investigate the setting of lower spurious correlation in this set of experiments. We study the 25\%, 50\% and 75\% spurious correlation cases along the 100\% correlation.

\begin{figure}[h]
\centering
\includegraphics[width=\textwidth]{influence_of_spurious_correlation}
\caption{Averaged accuracy $\Omega$ on 10 tasks over various amount of spurious correlation between spurious features and labels.}
\end{figure}

Fig. 6 we show that once we lower the spurious correlation, rehearsal and finetuning (baseline) become the best approaches. Those results indicate us the OOD baselines are most interesting in the very high spurious correlation setting but are not very interesting when the spurious correlation is lower or equal to 75\%. It might be quite counter-intuitive that finetuning is over the best baseline in a continual learning setting. Still, only the spurious correlation change in our scenario, so the full information to solve all tasks is contained in each task. It is then possible that with a lower spurious correlation finetuning works well.

5.4.2 Lowering the Support Amount

In our previous experiments, the data used for different tasks were exactly the same. This means that the shared support of original data is 100\%. However, we expect continual algorithms to learn with a lower amount of support. The support of a task is the percentage of the full original distribution within the task. We investigate in those experiments the influence that the support amount has on learning algorithms. We set the spurious correlation to 75\% in those experiments.

Remark 5.1 (add name). Lowering the support amount does not make only the task harder because there are fewer data per task, but also because it removes the full observability of data. It means that good/global features are no longer invariant and that good features can be available in some tasks but not others.

As it is designed in the SpuriousCIFAR2 scenario, each class (0 and 1) has 5 distributional mode corresponding to the 5 original classes. In the previous experiments, all the data for all those modes are available in all tasks only the spurious features changes from one task to another.

In those experiments, we reduce the support by subsampling the original data. We select the data of a subset of the CIFAR10 classes for each task. For example, we select only cars for class 0 and only deers for class 1, instead
of selecting airplanes, cars, trucks, ships and horses for class 0 and birds, cats, dogs, deers and frogs for class 1. Hence, if we use a support of 0.2 (i.e. 20%), we will only select the data of \(5 \times 0.2 = 1.0\) original classes for class 0 and one other for class 1. For simplicity’s sake, we will use only support compatible with the number of classes to have a round subset, i.e., \([0.2, 0.4, 0.6, 0.8, 1.0]\). At each task, the support is randomly sampled, hence the same original data can be in several tasks, but the spurious features will still be different for all tasks.

The support experiments results, illustrate in Fig. 7, show that in all support settings, the finetuning baseline and rehearsal are the best performing methods. On the other hand, contrary to what would be expected, the amount of support seems to not play an important role in the final performance, at least, in the range of support possible in our scenario. This is probably because doing replay converts a partially observable setting into a fully observable setting by simulating an iid distribution.

### 5.4.3 Potential Solutions to Lower Impact of Spurious Features

Figure 8: Canceling noisy spurious features with pre-trained models. Rehearsal, 100 samples per class for replay, 100 % spurious correlation, resnet pre-trained on CIFAR100 vs no pre-training. Rehearsal, 100 samples per class for replay, 50 % dropout in the features vs. no dropout.

A solution to not rely too much on spurious features is to force the model to learn/use more features. This can be achieved by adding surrogate loss, achieving transfer from trusted models or tasks. We show two potential
trivial solutions that could improve the results: a model pre-trained on a trusted task and a regularization strategy to maximize the number of representations learned (different from regularization methods designed to not forget).

**Assuming Spurious Correlation are noise**

We can use a pre-trained model on a trusted data source to ignore spurious features. For example, the spurious feature in our setting is noise, so if we use a pre-trained model on a known dataset such as CIFAR100, we can significantly improve results. This approach, experimented in Fig. 8a, shows clearly that using a pre-trained model can erase the problem of noisy spurious correlation. This solution is convenient, but it assumes we have a compatible trusted set of data (or a trusted model). It also assumes that the spurious features are not features that could be discriminative and are noise.

**Assuming Spurious Correlation are existing features**

Spurious features on one task can be good features for another one. For example, the color can be a spurious feature in some task and discriminative one in another task. Hence, a pre-trained model will not “filter” those spurious features and avoid relying on them while learning. A potential solution is not to try to ignore some features but to learn as many features as possible that could help solve the problem. A famous solution to maximize the features learned is **dropout**, and it has been widely experimented in continual learning [9, 19].

We experimented 0.25, 0.5, and 0.75 amount of dropout just before the last linear layer. However, unfortunately in our experiments, it did not show any improvement with dropout than without (cf. Fig. 8b).

Nevertheless, on a similar idea as dropout, the **spectral decoupling** approach is designed to address the gradient starvation problem. The gradient starvation problem arises when the loss is minimized by capturing only a subset of features relevant for the task, despite the presence of other predictive features that fail to be discovered [22]. Spectral decoupling is designed to discover supplementary features even when there is minimal train error. As dropout, it enables the possibility to learn additional representations that could help to improve test error. The experiment in section 5.3 illustrates in Fig. 5 indeed show that in the 100% spurious correlation experiment, this strategy greatly improves simple rehearsal proving the potential of the idea.

We proposed trivial solutions to illustrate how supplementary knowledge or assumption on the spurious features might help prevent or fix bad learning behavior. However, it would probably not work as easily in a setting with more complex spurious features.

In this section, we have investigated how algorithms learning continually can deal with spurious features. We created a benchmark with spurious features and empirically investigate algorithms performance when varying the correlation of spurious features with labels and the amount of support per task. In the next section, we will investigate local spurious features which are a type of spurious feature specific to continual learning. We will investigate if those features may cause performance decrease in continual learning algorithms.

### 6 Local Spurious Features

To investigate if local spurious features may cause performance decrease for continual learning algorithms, we design a setting where algorithms learn tasks independently and we test with all tasks together, to estimate if the features used within a task are generalizable. The setting is also designed such as forgetting can not cause performance decrease and interfere with the local spurious features problem.

#### 6.1 Setting

After experimenting with spurious features in an domain incremental environment, we experiment with the impact of local spurious features. The goal is to show that features learn in a task are not generalizable to the whole scenario.

We use the original CIFAR10, which we split into 5 tasks of 2 classes to create a class-incremental setting. We want to show that many features used to solve a given task are only local and not global. For this, we use a pre-trained model on CIFAR100, and we will train only a linear classifier on top. We will use a multi-head approach to see if the model learns local features. Hence, while training we only apply the softmax function to the outputs associated to the current task. We note the test performance in multi-head $A_{test\_local,softmax}$. We note that no forgetting can happen in this setting since the features extractor and the other heads are frozen. After training, we compare the test performance with the same model (i.e. the model trained with multi-head) but with the softmax applied on all outputs $A_{test\_global,softmax}$. It is similar to removing the access to the task index for inference.

In class-incremental, local features are sufficient in multi-head architectures, while for single head architecture, the global features are necessary [13].

Hence, the difference in performance will give us an insight into how local features are adapted to the whole classification task.

As this setting is only designed to assessing if local features learned by models are generalizable, and since no forgetting is possible, we only experiment with a finetuning approach. It is sufficient to make it possible to highlights the local spurious features problem that leads to bad feature selection.
6.2 Experiments

In those experiments, we investigate the influence of local features in class-incremental scenarios on CIFAR10. The question we would like to answer is: “Does local features learned by a linear layer are spurious features in class-incremental scenarios?”.

We report results in Figure 9. To understand the figure it is important to keep in mind that for single head and multi-heads results, only the inference methods change, the model and the weights are the same. The weights have been learned by a multi-head training for both results. Even so, we see that there is a huge gap between performance in multi-head and single head in the linear layer. Apart from the problem of feature selection, the gap could be explained by (1) the difference of difficulty of both evaluation (multi-head and single head), (2) an unbalance of bias and norms from different heads that could lead to bad performance in single head [17] (more details about this problem in appendix 11). However, if neither (1) or (2) are sufficient to explain the performance gap it would mean that the feature selection was bad, i.e. that the multi-head training selected local features that are not generalizable to more classes: spurious local features. We can note that forgetting is by design impossible here, so forgetting can not explain the drop in performance.

Concerning the performance gap, the comparison between single head and multi-heads is biased because the first is a 10-way classification (harder) while the latter is 5 binary classification (simpler). To estimate the gap in performance between both difficulty, we added a non-parametric method, MeanLayer as in [17] which is an nearest mean classifier (NMC). There is no feature selection in MeanLayer, the classifier only uses the mean of each class features. There is no problem with local features then. The difference of MeanLayer in multi-head and single head is a good proxy to estimate the difference of difficulty of both evaluations. The gap for MeanLayer explains then partly the gap for the linear layer but not entirely since the gap for the linear layer is significantly bigger (Fig. 9).

Concerning the potential unbalance of bias and norms, we compare the linear layer performance with the weightnorm layer from [17]. This layer does not use norm and bias for inference and is then insensitive to such imbalance (details in appendix 11). The similar results for linear layer and weightnorm show that the norm/bias unbalance is not a problem in our experiments and therefore, can not explain the performance gap.

To conclude, the gap in performance between single and multi-head is partly explained by the difference of difficulty of evaluations but this explanation is not sufficient. Therefore, we can conclude that the algorithm learned local spurious features to solve tasks. In this experience, we showed that the local features learned were spurious. The bad feature selection lead to a drop in performance when we used the weights learned in a single head fashion. These phenomena prove that the drop in performance in class-incremental is due to a bad feature selection and not necessarily to forgetting. This is a fundamental observation for future continual learning approaches.

Another interesting insight that this experiment gives is that contrary to experiments in section 5.4.3, using a pre-trained model does not offer a solution to local spurious features. A good feature extractor is then not sufficient for a good feature selection by the classifier.

7 Discussion

Spurious Features vs Local Spurious Features Spurious features and local spurious features lead to the same problem for learning algorithms: overfitting features that are not discriminative. The difference is that spurious
features are due to a covariate shift between training and test data, while local spurious features are due to the unavailability of all data while learning. Local spurious features are then, more specifically, a continual learning challenge.

**Solutions** The problem of spurious features and local spurious features being spurious lead to phenomena were forgetting is helpful to improve final performance [30] also denoted as graceful forgetting. Indeed, forgetting by reinitializing some weights gives the opportunity to escape a spurious local minima and relearn a better solution taking new data and knowledge into account. On a more general note, spurious features and local spurious features make ineffective approaches that are too rigid and unable to modify and fix previously learned features/knowledge.

**Benchmark** The scenario proposed in this paper has been designed to highlight the problem that spurious correlation might create or not in continual lifelong learning. This scenario plainly fulfills its task of disturbing continual learning algorithms, particularly in the 100% correlation setting. However, it can not be used as a benchmark to evaluate the robustness of algorithms. The spurious features are very simple, and a simple ad hoc processing of data could solve this scenario, i.e., encoding data with a pre-trained model as in 8a. A proper benchmark to assess robustness to spurious correlation would propose spurious features easy to learn by the model but harder to detect or ignore than simple squares of color.

8 Conclusion

Identifying general features in continual learning necessitates to both be able to deal with spurious features and local spurious features. This paper investigates first the impact of spurious features on continual learning. Algorithms easily overfit spurious features for one or several tasks, leading to poor generalization. Our goal was to investigate if continual learning algorithms can benefit from the variation of the spurious features through time to ignore them. Our results show that a classical continual learning approach such as rehearsal can deal with spurious features until a certain level of correlation with labels. However, rehearsal is not enough once the spuriousness reaches 100% of correlation with training labels, and alternative approaches should be found.

In a second time, we investigate the problem of local spurious features. Those features correlate spuriously with labels, not because of a covariate shift between train and test but because all data is not available at once. We show that algorithm can easily overfit local spurious features. Consequently the solution learned to solve a task becomes outdated when new data arrives.

The local spurious features lead algorithms to learn solutions that are not generalizable. It leads to a significant drop in performance while learning new tasks. In the continual learning literature, performance decrease is generally attributed to catastrophic forgetting. Our results show that local spurious features problem seems to play also a major role. More research is needed to understand better the impact of local spurious features along with catastrophic forgetting. Understanding this phenomenon is critical to better target forgetting and feature selection and address them properly.

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9 Samples Support Experiments

Figure 10: Samples for support experiences, here with 20% support, i.e. the data of only two of the original classes in each task.

10 Hyper-Parameters selection

For a fair comparison between algorithms originally designed for continual learning, such as replay and OOD algorithms, we conduct the hyper-parameter search more intensively for OOD approaches. For each OOD approach, we search for the best hyper-parameters in the range proposed in the DomainBed GitHub repository [1]. We also searched for the best learning rate with the bayesian method of wandb [3]. We approximately 100 runs for each OOD baselines to select hyper-parameters. The scenario for hyper-parameters selection was an OOD setting with 5 environments of SpuriousCIFAR2 with 75% correlation but all simultaneously available (with no continual stream of tasks).

The hyper-parameters for rehearsal and finetuning (baseline), have been selected on a finetuning training in a single task setting with 75% of correlation. The number of samples per class for replay has been selected on a 5 task SpuriousCifar2 scenario with 75% of correlation.

11 Bias Norm imbalance

As described in [17]: A linear layer is parameterized by a weight matrix $A$ and bias vector $b$, respectively of size $N \times h$ and $N$, where $h$ is the size of the latent vector (the activations of the penultimate layer) and $N$ is the number of classes. For $z$ a latent vector, the output layer computes the operation $o = Az + b$. We can formulate this operation for a single class $i$ with $\langle z, A_i \rangle + b_i = o_i$, where $\langle \cdot, \cdot \rangle$ is the euclidean scalar product, $A_i$ is the $i$th row of the weight matrix viewed as a vector and $b_i$ is the corresponding scalar bias.

It can be rewritten:

$$||z|| \cdot |A_i| \cdot \cos(\angle(z, A_i)) + b_i = o_i \tag{4}$$

Where $\angle(\cdot, \cdot)$ is the angle between two vectors and $||\cdot||$ denotes here the euclidean norm of a vector.

Then, at inference time, $y_i = \text{argmax}_i(o_i)$ rely on the norm of $||A_i||$ and on the bias $b_i$. Within a single task, i.e. within a single head in a multi-head setting, $||A_i||$ and $b_i$ are balanced to predict class correctly. However, we can not ensure that $||A_i||$ and $b_i$ will are not biased from one head to another.

To avoid unbalance for bias and norm for inference, [17] proposed the weightnorm layer where: $||z|| \cdot \cos(\angle(z, A_i)) = o_i$ and show that this layer in efficient in learning in incremental and lifelong settings.

[1] https://github.com/facebookresearch/DomainBed