Exploring Concept Drift Visualization and Explanation in Image Streams

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Abstract. In the rapidly evolving field of Machine Learning applied to data streams, where information arrives continuously and models must adapt in real-time, drift detection has emerged as a critical component for maintaining model accuracy and reliability. While much attention has been given to structured data, the challenge of handling real-time image streams remains comparatively underexplored, despite its vital role in numerous applications. This study addresses this gap by exploring innovative approaches to visualize and explain drift in image streams. We propose a novel method that leverages zero-shot classification capabilities of a pre-trained ResNet-50 architecture to visualize potential changes within the stream. Additionally, we investigate the application of ResNet-50 in combination with Uniform Manifold Approximation and Projection (UMAP). This hybrid approach aims to identify and visualize drift in high-dimensional image data by projecting it onto a lower-dimensional space, facilitating easier interpretation and analysis of evolving patterns over time. Preliminary results on the CLEAR10 dataset, the first benchmark with a natural temporal evolution of visual concepts, showcase potential applications for drift monitoring in image streams. These findings present a promising avenue for further research and development, aiming to solidify the integration of these methodologies for improved drift detection and overall models performance in dynamic data contexts.

Keywords: Image classification · Data streams · Concept drift.

1 Introduction

Continuous learning is increasingly recognized in Machine Learning and Artificial Intelligence, especially with the integration of sensor networks and the Internet of Things. Real-time applications demand immediate online learning for each instance, posing challenges in processing entire datasets due to resource constraints. Streaming Machine Learning (SML) has emerged as a pivotal paradigm [1]. SML operates under unique constraints: (i) single-pass learning, observing each item once; (ii) minimal processing time per item; (iii) constrained memory usage, ideally sub-linear with stream length; (iv) real-time provision of answers; and (v) adaptation to dynamic data sources' evolution over time.

While the SML community has extensively explored classifiers for simpler data streams [9], there is a notable gap in addressing challenges posed by complex and high-dimensional data streams. SML research has primarily focused on tabular datasets due to computational constraints and the need for efficient single-pass processing in highly non-stationary scenarios. With fewer features, these datasets serve as foundational testing grounds for SML algorithms. However, streams with intricate spatio-temporal dependencies, common in image recognition and sensor networks, require more sophisticated methodologies for visualizing and detecting evolving patterns.

Deep neural networks (DNNs) are widely recognized for their dominance in complex domains like image classification, particularly in tasks involving semantic extraction from sensor data like cameras [14]. Despite their efficacy, training DNNs requires extensive data and iterations, making them unsuitable for streaming data scenarios where class distributions or labels may change. Conventional DNNs struggle with adapting to incremental updates or swift learning from individual instances due to the stability-plasticity dilemma [10]. However, they can be valuable in inference-only mode by effectively extracting meaningful features.

In this preliminary study, we propose two methodologies. The first approach utilizes zero-shot classification with pre-trained deep neural networks (DNNs) to study evolving patterns in the image stream. The second one leverages pre-trained DNNs to extract low-dimensional features from images, which are then visualized using dimensionality reduction techniques such as Uniform Manifold Approximation and Projection (UMAP) [11]. We conduct preliminary experiments on the CLEAR10 dataset [7], the first benchmark with a natural temporal evolution of visual concepts, showcasing potential applications for drift monitoring in image streams. All data streams and algorithms used in this paper are available online [1] as a publicly available benchmark to help other researchers to reproduce the results shown in this study or the development of new algorithms.

The remainder of this paper is organized as follows. Section 2 presents relevant works on concept drift detection, explanation, and visualization. Section 3 details the proposed methodologies, while Section 4 introduces the CLEAR10 dataset and discusses initial findings. Finally, Section 5 summarizes our findings and outlines future research directions for investigating concept drift in the context of image streams.

2 Related Works

The phenomenon of concept drift, characterized by changes in the statistical properties of data over time, has been extensively studied within the area of Machine Learning, particularly in the context of streaming data. The research community has primarily focused on strategies for detecting and adapting to concept drift, emphasizing the critical importance of timely detection to maintain model accuracy [4,3,9]. As machine learning models are deployed in dynamic environments, their performance can degrade if they fail to adapt to these changes.

[1] `https://github.com/gziffer/image-stream-drift-analysis`

This necessitates a robust understanding of concept drift's underlying causes and mechanisms.

In recent years, explainability has emerged as a significant area of research, particularly regarding the need for models to provide interpretable outputs [13]. However, the development of more complex explanation methods specifically tailored for concept drift remains limited. Various approaches have been proposed to detect and quantify drift [18,9,16], localize it in space [8,9,5,16], and visualize its effects using feature-wise representations of drift [12,18,17]. Nevertheless, these techniques often encounter challenges when dealing with high-dimensional data or non-semantic features, highlighting the need for further research.

A notable contribution to the understanding of concept drift explored model-based explanations of concept drift [6]. The authors proposed a methodology that simplifies the explanation of concept drift by framing it in terms of models trained to extract relevant information regarding the drift. This approach facilitates the use of a diverse array of explanation schemes, allowing researchers to select the most appropriate method for addressing specific drift-related challenges. By characterizing concept drift through the changes in spatial features using various explanation techniques, the authors aimed to provide human-understandable descriptions of how and where drift manifests, ultimately enhancing the acceptance of lifelong learning models.

Only few works concentrated on the application of concept drift detection and visualization techniques to image streams, as most studies have focused on structured data. Yang et al. [19] discussed visual analytics approaches for diagnosing concept drift, suggesting that traditional drift detection methods can be effectively adapted for image classification tasks. However, the challenges posed by high-dimensional unstructured data streams are still largely unexplored. This area requires focused research to address the evolution of image features over time and the resulting impact on the accuracy of streaming classifiers.

3 Proposed Methods

In this section, we present the methodologies proposed for conducting drift analysis in image streams. The approach involves leveraging pre-trained neural networks for feature extraction, followed by the application of UMAP as the chosen technique for dimensionality reduction. This combination aims to effectively capture and analyze changes in the underlying data distribution over time.

Zero-Shot Classification for Drift Visualization The first approach leverages zero-shot classification using pre-trained deep neural networks (DNNs) to monitor and visualize drift in image streams. In this method, a neural network trained on a broad and diverse dataset, such as ImageNet, is employed in an inference-only mode without any additional fine-tuning for the specific data stream being analyzed. This design choice capitalizes on the generalization capability of the pre-trained model, allowing it to recognize and classify a wide range of image categories even when faced with new and previously unseen data.

The pre-trained DNN is directly applied to classify incoming images, and the resulting predicted classes are continuously analyzed to observe how their distribution evolves over time. By tracking changes in the distribution of these predictions, we can identify potential drift within the data stream. Since the model operates without fine-tuning, its predictions are based solely on its initial training, making any shifts in class distribution particularly valuable for detecting drift. By cross-referencing the predicted classes with those in the model's original training dataset, we can assess whether the model is encountering familiar or entirely new categories. This capability is crucial for understanding if the model can recognize classes independently of any further training.

This approach is especially effective for identifying drifts that involve the emergence of new classes or the reappearance of previously unseen ones within the data stream. The pre-trained DNN's ability to generalize across a wide spectrum of categories provides a direct and efficient method for tracking changes in data distribution, making it highly useful in scenarios where quickly detecting shifts in data patterns is critical. By utilizing the model in an inference-only mode, the approach remains robust to new data while avoiding the complexities and computational overhead associated with fine-tuning. This ensures that the model can adapt to evolving data streams without compromising its performance, offering a scalable and practical solution for real-time drift detection.

Feature Extraction and UMAP for Drift Analysis The second approach involves feature extraction from a pre-trained DNN, but instead of using the final classification layer, we focus on the intermediate embeddings. These embeddings represent low-dimensional features that capture the essential characteristics of the images. After extracting these features, we apply Uniform Manifold Approximation and Projection (UMAP) [11] for dimensionality reduction. UMAP is chosen for its ability to maintain the temporal orientation of the data, which is crucial for understanding the evolution of patterns over time.

This method leverages the robust feature extraction capabilities of deep learning and the efficiency and interpretability of UMAP. By visualizing the reduced-dimensional embeddings, we can detect and visualize distributional shifts in the feature space. Additionally, this methodology can be extended by integrating distance metrics in the UMAP embedding space, such as the Wasserstein distance, to quantify the variation in the position of data points. This approach can be used both for real-time drift detection and for exploratory analysis of potential drifts in image streams.

4 Results

4.1 CLEAR10 Dataset

CLEAR10, a benchmark designed for continuous learning of real-world images, introduces a novel approach by focusing on the natural temporal evolution of visual concepts in Internet images. Leveraging the YFCC100M [15] dataset and

Fig. 1. Display of the temporal evolution of visual concepts Computer, Bus, Camera, Hockey and Cosplay in CLEAR10 dataset [7].

timestamps of images spanning 2004 to 2014, CLEAR10 organizes the data into a temporal stream divided into 11 'buckets'. Each bucket, representing a specific time period, features a subset of 11 temporally dynamic classes. These classes include 10 illustrative categories (e.g., baseball, bus, camera, cosplay, dress, hockey, laptop, racing, soccer, sweater) and an additional background class, with 300 labeled images per class, as shown in Fig. 1.

Analyzing the evolution of visual concepts within the CLEAR10 benchmark spanning 2004 to 2014 offers a compelling perspective for applying adaptive SML classifiers. The dynamic nature of visual content over this timeframe encapsulates technological advancements and shifting trends, providing an intricate stream of data. From the transition in camera technologies, exemplified by the progression from Canon EOS 30D to Canon EOS 6D, to the transformation of the term "camera" itself (from traditional stand-alone devices to integration in smartphones like the iPhone 5 [7]) these changes pose unique challenges for real-time learning systems. Consequently, the CLEAR10 benchmark becomes a valuable testbed, as it necessitates continuous adaptation to evolving visual landscapes, reflecting the real-world challenges faced by systems operating in dynamic and temporally evolving environments.

4.2 Results

Figure 2 shows the visualization using the zero-shot classification methodology. We utilized a pre-trained ResNet-50 network trained on ImageNet [2]. On the x-axis of the figure, the CLEAR10 classes are displayed, each divided by the bucket (year) of the stream, while the y-axis shows the ImageNet classes. We have cropped the figure to display only from the 400th class onwards, as there were no significant selections below this point. The diameter and color of the circles

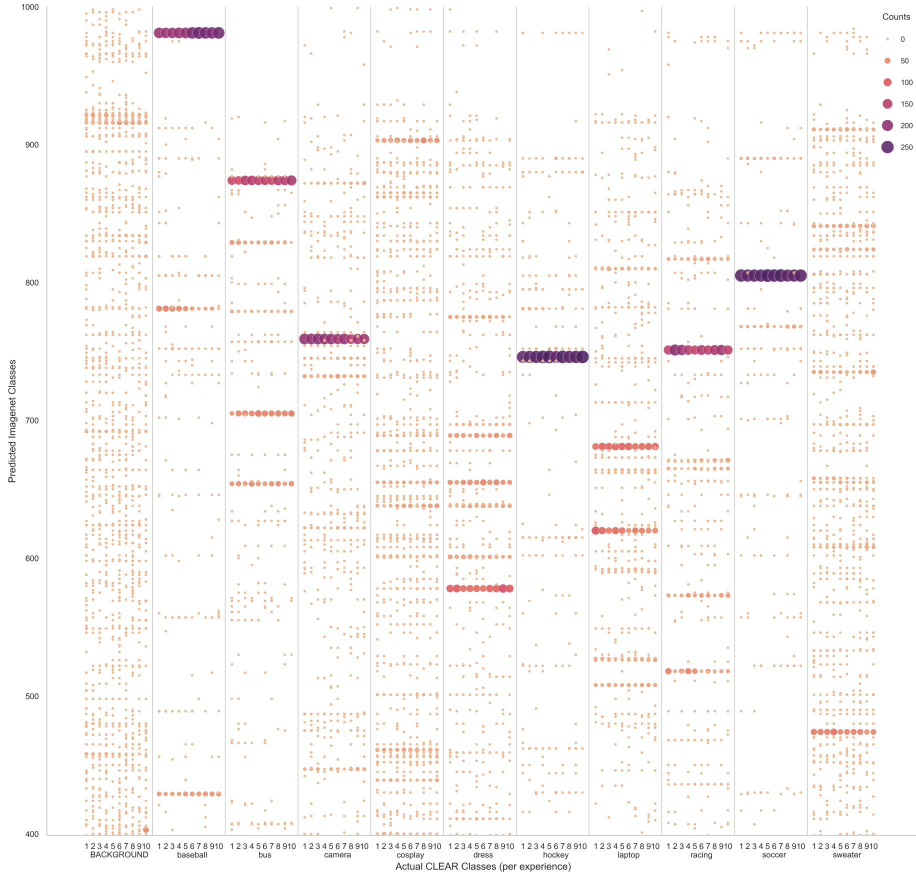

Fig. 2. Visualization of the CLEAR10 classes using a Resnet50 pretrained on the ImageNet dataset.

indicate how frequently a particular ImageNet class (among the 1000 classes) was predicted by the pre-trained network for the given CLEAR10 images.

Several insights can be drawn from these results. Three CLEAR10 classes, baseball, hockey, and soccer, have a predominant ImageNet class, with over 250 predictions per bucket out of 300 images per class per bucket. This suggests that for these three CLEAR10 classes, a single ImageNet class maps very well, and the lack of significant variation over the years indicates that these classes have mostly stayed the same. Notably, we are using a model that is not continuously learning, so we can evaluate how patterns change relative to a pre-learned pattern.

Moreover, a notable observation pertains to the Background class in the first column. As expected, no dominant class emerges, suggesting ongoing changes in these images over the years. Another challenging category is cosplay, which is absent from ImageNet and frequently categorized as various types of cloth-

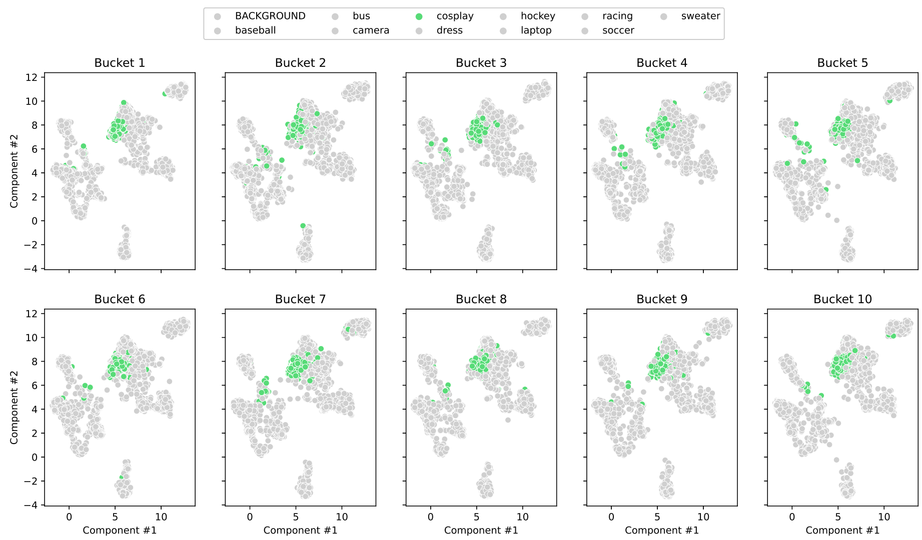

Fig. 3. Visualization of the Cosplay class using two components of UMAP.

ing. Particularly, this class is often predicted as the same ImageNet class as CLEAR10 dress class, indicating a notable pattern possibly indicative of gradual and recurrent drift. This is supported by the fluctuation in the number of predictions over time, implying a resemblance among non-consecutive images.

Finally, Fig. 3 depicts the embedding visualization of the cosplay class across the ten buckets. In this scenario, UMAP was initially fitted using data from the first bucket and subsequently applied to data from subsequent years, mimicking a real-world scenario where the feature extraction pipeline is updated only when drift is detected. Remarkably, the cosplay class maintains a relatively stable position throughout the period, indicating potential evidence of gradual drift at most, particularly observable in instances where notable changes in distances occur.

5 Conclusion

This study underscores the importance of drift analysis in image streams, presenting two approaches for monitoring and detecting distributional shifts while enhancing explainability. By leveraging pre-trained ResNet-50 deep neural networks, our methodologies extract more meaningful features, rendering them more conducive to thorough analysis and interpretation. Conversely, the feature extraction and UMAP visualization approach facilitate the visualization of distributional shifts in the feature space, establishing a robust framework for drift analysis in streaming image data. Our exploration of the CLEAR10 dataset yields invaluable insights into the evolving nature of visual concepts over time, thereby elucidating the challenges inherent in non-stationary image streams.

As for future work, it is imperative to conduct more rigorous testing to validate the efficacy of our methodologies. Additionally, an intriguing avenue for further development lies in transforming the UMAP approach into a drift detection algorithm for image streams. Given that we already have the feature space and distances between points, it becomes straightforward to ascertain whether distances are increasing, thus simplifying the detection process.

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