Abstract

The common self-supervised pre-training practice requires collecting massive unlabeled data together and then trains a representation model, dubbed joint training. However, in real-world scenarios where data are collected in a streaming fashion, the joint training scheme is usually storage-heavy and time-consuming. A more efficient alternative is to train a model continually with streaming data, dubbed sequential training. Nevertheless, it is unclear how well sequential self-supervised pre-training performs with streaming data. In this paper, we conduct thorough experiments to investigate self-supervised pre-training with streaming data. Specifically, we evaluate the transfer performance of sequential self-supervised pre-training with four different data sequences on three different downstream tasks and make comparisons with joint self-supervised pre-training. Surprisingly, we find sequential self-supervised learning exhibits almost the same performance as the joint training when the distribution shifts within streaming data are mild. Even for data sequences with large distribution shifts, sequential self-supervised training with simple techniques, e.g., parameter regularization or data replay, still performs comparably to joint training. Based on our findings, we recommend using sequential self-supervised training as a more efficient yet performance-competitive representation learning practice for real-world applications.

1. Introduction

Relying on supervised learning with large-scale labeled data, deep neural networks (DNNs) are able to extract transferable features beneficial to various visual tasks [12, 61]. As a result, it has been a popular paradigm to first pre-train a DNNs model on a large-scale labeled database (e.g., ImageNet [49]) and then transfer the learned representations to target downstream tasks. However, supervised pre-training requires massive labeled data, which are usually difficult to collect and annotate.

To exempt expensive human labeling, existing works have resorted to self-supervised learning (SSL) with large-scale unlabeled data. SSL aims to learn useful features via solving various pretext tasks [40, 16, 5, 19, 18] using labels generated from the unlabeled data themselves. Recent advances in SSL [18, 6] demonstrate comparable or even better transfer performance on various downstream tasks, compared with supervised learning.

Although SSL waives the cost of human labeling, it usually requires massive unlabeled data to learn a good representation model. Meanwhile, it is desirable to leverage significantly large-scale unlabeled data, e.g., billion-scale data to pre-train a strong model [19]. However, such a large amount of unlabeled data are not easy to obtain at a time. In realistic scenarios, unlabeled data are usually streaming, generated and collected sequentially batch by batch. How
to leverage such streaming data to pre-train a strong self-supervised representation model is well-worth studying.

The common pre-training scheme with SSL collects massive unlabeled data together and trains a self-supervised representation model jointly using these data, dubbed joint training. When data come in a streaming fashion, the joint training scheme needs to store all seen data batches and retrain the representation model with both each new data batch and stored old data, which is significantly storage-heavy and time-consuming. For example, it takes about one week to train MoCo-v2 [9] on ImageNet for 300 epochs with eight Nvidia V100 GPUs. To sum up, the joint training scheme is quite inefficient for SSL with streaming data.

An efficient learning scheme in supervised learning with streaming data is to train a supervised model continually using the data stream, dubbed sequential training. Sequential training is assumed to suffer from catastrophic forgetting in supervised learning [17, 22, 35], leading to significant performance degradation of previous tasks. However, whether self-supervised pre-training with streaming data suffers the similar degradation of transfer performance on downstream tasks is still unclear.

In this work, we empirically study how well SSL representations transfer to downstream tasks under realistic sequential training settings, where a pre-trained model is continually learned with zero or limited reference to past data. Specifically, we consider four diverse sequential training scenarios with different degrees of data distribution shifts, i.e., the instance incremental sequence, the random class incremental sequence, the distant class incremental sequence, and the domain incremental sequence. For the illustration purpose, we choose a prevailing self-supervised learning method MoCo-v2 [9] for empirical studies. Following [13], the transfer performance of pre-trained models are evaluated on 12 image classification datasets [24] and the Pascal VOC [14] detection. Surprisingly, we find:

- Self-supervised learning has a significantly smaller transfer performance gap between joint training and sequential training than supervised pre-training under all the four sequential training scenarios.
- Specifically, sequential SSL exhibits almost the same transfer performance as the joint training, as shown in Figure 1(a)-(c), for both instance incremental sequence and random class incremental sequence while requiring significantly less training time and data storage, as shown in Figure 1(d).
- For streaming data with large distribution shifts, e.g., the distant class incremental sequence, sequential self-supervised learning transfers slightly worse than joint training. This minor performance gap, nevertheless, can be mitigated effectively and efficiently with unsupervised regularization [1] and simple data replay.

The above observations suggest that, the common joint training practice may be unnecessary for SSL to obtain a good representation model with streaming data. Instead, sequential self-supervised pre-training is performance-competitive but more time-efficient and storage-saving, well worth considering as common practice for self-supervised pre-training with streaming data.

2. Related Work

Self-supervised learning (SSL). SSL learns useful representations by solving various pretext tasks using supervisions generated from unlabeled training data, e.g., predicting rotations [16], solving jigsaw puzzles [40], predicting colorization [28], predicting cluster assignments [5] and solving instance discrimination [57, 7, 19, 18]. Recently, instance discrimination has become the most popular pretext task for SSL, which motivates various contrastive SSL methods [53, 7, 19, 9, 37, 54, 59]. Contrastive SSL usually leverages a contrastive loss [41] to maximize the similarity of features from the same image and minimize the similarity of features from different images, where massive pairwise comparisons among different images are required. Many strategies are proposed to improve contrastive learning, including maintaining a memory bank of all features [57], using a large batch size [7] and using momentum encoders [19, 9]. To further improve the representation model, recent studies of SSL have proposed to pre-train a representation model with increasingly large datasets such as YFCC 100M [52] or even Instagram 1B [32]. Despite the desirable transfer performance [19], in realistic scenarios, it is not easy to acquire massive data at a time and unlabeled data are mostly streaming. However, how to efficiently and effectively perform SSL with streaming data remains open, which motivates our study.

Pre-training and fine-tuning. Pre-training a deep network on a large dataset e.g., ImageNet and then fine-tuning it on downstream tasks is a common scheme in deep learning [27, 20]. The mainstream method for pre-training is supervised learning [24], while self-supervised learning has attracted increasing attention as it does not require substantial data annotations [7, 19, 9, 8]. Most existing methods for fine-tuning [29, 30] are devised for supervised pre-trained models, while a recent study [63] starts to pay attention to the fine-tuning of self-supervised pre-trained models. However, all above works study the pre-training or fine-tuning problem under the joint training setting, few have explored self-supervised pre-training with streaming data and how well it performs on downstream tasks.

Continual learning. Existing studies of continual learning (CL) [11] mainly focus on supervised tasks and can be summarized into three categories, including regularization, replay and parameter-isolation. In regularization-based CL, knowledge preserving is achieved by regularizing the pa-
rameter posterior of the new task not to deviate drastically from the prior \([1, 22, 62]\). Replay-based CL methods overcome forgetting by saving samples of previous tasks in a replay buffer \([46, 48, 31, 55]\) and using them to regularize the learning of new tasks. Last, isolation-based CL methods leverage different parameters for learning each task to preserve the learned knowledge \([51, 34]\). Although works \([45, 2]\) explore continual learning for some specific unsupervised tasks, few have studied the transfer performance of sequential self-supervised representation learning.

3. Problem Setting

We aim to investigate the transfer performance of self-supervised pre-training with streaming data. To this end, we first introduce four types of realistic streaming data in Section 3.1. Then, we introduce two schemes of self-supervised pre-training, i.e., joint training and sequential training, in Section 3.2. At last, in Section 3.3, we introduce three different downstream tasks which are used evaluate pre-trained representation models.

3.1. Streaming data

Formally, we consider the unlabeled dataset \(D = \bigcup_{b=1}^{B} D_b\) with \(B\) batches of data, where \(D_b = \bigcup \{x_i\}\) represents the \(b\)-th data batch in the stream. Without loss of generality, we assume that these data come from \(C\) classes although the labels are unavailable for model training. To mimic various data collection schemes in realistic applications, we consider streaming data with four different distributions, including the instance incremental sequence, the random class incremental sequence, the distant class incremental sequence, and the domain incremental sequence. See Figure 2 as an illustration.

**Instance incremental sequence.** We first consider the sequential training of new instance \([42]\). It assumes that streaming data are independent and identically distributed (IID), where each sequence batch contains all the \(C\) classes but new instances come in sequentially.

**Random class incremental sequence.** We further consider the class incremental scenario, where new classes are introduced in the coming data \([42]\). Such a data sequence assumes that different data batches contain images from disjoint classes, and there is no overlapping of classes between data batches.

**Distant class incremental sequence.** Extending from the random class incremental sequence, we intentionally split the data classes w.r.t. the semantic similarity of classes to enlarge the data distribution gaps among batches. In particular, images in the same data batch share similar semantics while images from different data batches are semantically dissimilar. This setting is designed to evaluate how well self-supervised pre-training performs on streaming data with large data distribution shifts.

**Domain incremental sequence.** Complementary to the above settings, we also consider a domain-incremental setting, where data batches in the stream come from different image domains. For example, the first data batch is realistic photos while the second data batch are paintings. Such a data sequence mimics streaming data with domain distribution shifts, where different data batches in the sequence may share the same classes or similar semantics.

3.2. Self-supervised pre-training

For the illustration purpose, we adopt the prevailing SSL method, MoCo-v2 \([9]\), to investigate the transfer performance of SSL with streaming data. See Appendix A for more details about MoCo-v2.

**Sequential training.** In sequential training, data samples used for model training are divided into disjoint batches, i.e., \(D = \bigcup_{b=1}^{B} D_b\), where \(B\) is the total number of batches. Here, a batch of data refers to a split of the streaming data, rather than a mini-batch in the gradient descent training process. In sequential self-supervised pre-training, both the representation network \(f_\theta\) and the projection head \(f_w\) are continually trained. Specifically, the \(b\)-th time sequential training starts from the pre-trained network including \(f_\theta^{b-1}\) and \(f_w^{b-1}\), only involving samples of data batch \(D_b\) in the model training. When the \(b\)-th time training finishes, only \(f_\theta^b\) and \(f_w^b\) are saved for sequential learning with next independent data batch. Given the same training epoch, sequential training is much more efficient than joint training as only new data are used for the continual pre-training at each batch. Continual learning techniques including data replay and unsupervised parameter regularization methods e.g. Memory Aware Synapses (MAS) \([1]\) may be used to further improve the performance of sequential training. See Appendix B for details about continual learning methods.
**Joint training.** In joint training, all available data are randomly shuffled to jointly train a model until convergence. Joint training is the common practice in SSL [18, 6]. As for pre-training with streaming data, each data batch has a joint training result. At \( b \)-th data batch, joint training requires all previously seen data batches, i.e., \( \{D_1, \ldots, D_{b-1}, D_b\} \), for jointly training a representation network \( f_b \) from scratch. When the data sequence is long and each data batch has a large amount of data, joint training is very storage-heavy and time-consuming.

### 3.3. Downstream tasks

To thoroughly evaluate the transfer learning ability of SSL pre-trained models with streaming data, we evaluate them on three typical downstream tasks, including many-shot classification, few-shot classification and detection.

**Many-shot classification.** Many-shot classification is a widely used evaluation protocol [8, 19]. To evaluate the pre-trained representations, a linear classifier is directly added to the pre-trained feature encoder. During the downstream task evaluation, only the added linear classifier is fine-tuned using the downstream training data while the feature encoder is frozen. In this way, the downstream transfer performance can directly reflect the generalization ability of the pre-trained representation models.

**Few-shot classification.** Few-shot classification reflects how well the pre-trained models perform on downstream tasks in the few-shot learning regime. Specifically, we consider 5-way 5-shot few-shot tasks on 11 downstream classification datasets, following the few-shot setting in [13].

**Detection.** To further evaluate the transfer ability of the pre-trained models on more downstream scenarios, we consider object detection as a downstream task, where the fine-grained spatial location information is more important, compared with classification tasks. To be specific, we follow the settings in [19], i.e., adopting the Faster-RCNN [47] with a backbone of R50-dilated-C5 and fine-tuning all layers including the pre-trained representation network.

### 4. Experiments

#### 4.1. Implementation details

**Streaming data.** We first consider ImageNet [49] as the streaming data and split it into 4 disjoint data batches, which means the data sequence length is \( B = 4 \). For the instance incremental sequence, we randomly shuffle and split all samples into four IID parts. For the random class incremental sequence, we randomly split ImageNet into four disjoint data batches with each batch having 250 classes. For the distant class incremental sequence, inspired by [21], we split ImageNet into four class-even batches according to WordNet Tree [36] while maximize the semantic dissimilarity across splits. In this case, the labels of data in different splits do not have common parent nodes under the ninth level of taxonomy. Finally, to obtain a domain incremental sequence, we adopt a multi-domain dataset called DomainNet [50] for pre-training. Following [50], we evenly choose samples from four domains including Real, Clipart, Sketch and Painting. See Appendix C for more detailed descriptions of the above data sequences.
**Pre-training.** For self-supervised pre-training, we follow the protocol of MoCo-v2 [9], i.e., using the standard ResNet50 backbone [20]. The implementation is based on OpenSelfSup\(^1\). For both joint training and sequential training, the number of training epochs is 200, where the convergence of loss is observed. For instance incremental data and random class incremental streaming data, we consider one random sequence as the data are randomly divided. While for distant class incremental data, we experiment with different sequences of data batches. In particular, considered sequences are obtained through right circular shift operations. That is to say, after splitting all the data into four batches A, B, C and D, four sequences, namely A-B-C-D, B-C-D-A, C-D-A-B and D-A-B-C are used for the sequential pre-training a representation model. The results from different sequences are averaged to obtain the final performance. For comparison, supervised pre-training is also implemented using OpenSelfSup following the recommended training protocol of ImageNet. For supervised pre-training, the classifier layer is reset at a new data batch.

**Transfer learning.** We evaluate the transfer performance of the pre-trained models using three different down-stream tasks. Following [7], we consider 12 diverse image classification datasets including Food-101 [4], CIFAR10 [26], CIFAR100 [26], Birdsnap [3], SUN397 [58], Standard Cars [25], FGVC Aircraft [33], VOC2007 [14], DTD [10], Oxford-IIIT Pets [43], Caltech-101 [15] and Oxford 102 Flowers [39]. On these datasets, we evaluate the pre-trained models via the many-shot classification and the few-shot classification (except VOC2007). Both classification protocols are the same as [13]. In addition, we evaluate the pre-trained models on the PASCAL VOC detection task, following the same transfer protocol of MoCo [19]. The training data of detection come from VOC2007 and VOC2012, and the test data come from VOC2007. See Appendix G for detailed hyper-parameters.

### 4.2. Results of transfer learning

We first compare the transfer performance on various downstream tasks between sequential SSL and joint SSL. Furthermore, we make comparisons between self-supervised pre-training and supervised pre-training on various types of streaming data.

**Instance incremental sequence.** Transfer results of self-supervised pre-training with the instance incremental sequence are evaluated on all three downstream tasks. For results of both many-shot classification and few-shot classification in Figure 3, we find sequential training performs comparably with joint training on all downstream datasets, with the average performance gap between sequential training and joint training less than 1%. Results of VOC detection in Figure 5(a) also show a similar observation. Generally, for the instance incremental sequence, sequential SSL exhibits comparable transfer performance to joint SSL on various downstream tasks.

**Random class incremental sequence.** As for the random class incremental sequence, transfer results on all three downstream tasks are illustrated in Figure 4 and Figure 5(b), respectively. Similarly, we find that, for the random class incremental sequence, the transfer performance gap between

\(^1\)https://github.com/open-mmlab/OpenSelfSup
sequential self-supervised pre-training and joint training is negligible under all three evaluation tasks.

![Figure 5](image-url)

Figure 5. Comparisons of transfer performance between sequential training (ST) and joint training (JT) for self-supervised pre-training on the detection task.

**Distant class incremental sequence.** Three downstream tasks are evaluated for the challenging distant class incremental sequence. For detection results in Figure 5(c), joint self-supervised training slightly outperforms sequential self-supervised learning by about 1%. However, as for the many-shot and few-shot evaluation in Figure 6, we observe an obvious transfer performance drop up to 5% on average, from joint SSL to sequential SSL. Considering large data distribution shifts among batches, we adopt simple continual learning techniques, including data replay and MAS [1], to investigate the possible performance improvement. When using data replay, we randomly select 10% data from the previous batches and mix the sampled data with the new batch of data for training. See Appendix D for detailed implementations of MAS and data replay. We also consider the combination of MAS and data replay, which is referred to as MAS+ in the experiments. Fortunately, the obvious performance drop of sequential SSL can be effectively mitigated by MAS+. MAS+ helps the sequential SSL effectively reduce the performance drop to be less than 2% on average for both many-shot and few-shot evaluation.

**Domain incremental sequence.** We evaluate SSL with the domain incremental data sequence by the few-shot classification task and show results in Figure 7. The four domains in the sequence are assumed to have large distribution shifts among each other [44] and are widely used by transfer learning research [38]. Surprisingly, sequential training is slightly better than joint training on average and keeps the leading place for 6 out of 11 downstream datasets. Such results demonstrate that sequential SSL can tolerate large domain distribution shifts within the streaming data. To further evaluate how well sequential SSL performs on the data sequence with larger domain distribution shifts, we add another significantly different domain named ‘quickdraw’, obtaining a five-domain data sequence. For this challenging five-domain sequence, sequential self-supervised pre-training witness an evident performance gap from the joint training. Fortunately, once considering the simple data replay strategy, sequential SSL shows comparable transfer performance to joint SSL on average. See Appendix E for more results on DomainNet.

To sum up, we find it is feasible to perform sequential self-supervised pre-training on streaming data like the instance incremental sequence, the random class incremental sequence, and the common domain incremental sequence, with negligible performance drop from joint pre-training. Moreover, with simple parameter regularization or data replay, sequential self-supervised pre-training can have competitive performance on complex streaming data like the distant class incremental sequence.

**Comparisons with supervised learning.** We further compare supervised learning (SL) and SSL in terms of the transfer performance. In Figure 3, Figure 4, and Figure 6, we illustrate the average transfer results. In Table 1, we exhibit the mean accuracy gap between sequential training and joint training under the many-shot evaluation. For data with negligible distribution shifts, SL exhibits an obvious accuracy gap while SSL has a negligible accuracy gap. For data with mild distribution shifts, SL exhibits a much larger accuracy gap while SSL still keeps the negligible accuracy gap. For data with large distribution shifts, SL still shows a large accuracy gap and SSL sees an evident accuracy gap. But such an accuracy gap of SSL can be effectively mitigated with simple continual learning methods. Generally, in the sequential training process, supervised learning (SL) suffers from significantly larger transfer performance degradation from the joint training than SSL.

Table 1. Transfer performance gap between sequential training and joint training under many-shot evaluation. The lower, the better.

| Accuracy gap (%) / Batch | 2    | 3    | 4    |
|-------------------------|------|------|------|
| SL-ST (Instance)        | 2.26 | 3.27 | 4.83 |
| ST (Instance)           | 0.41 | 1.02 | 1.04 |
| SL-ST (Random class)    | 6.51 | 10.25| 11.59|
| ST (Random class)       | 0.31 | 0.37 | 1.36 |
| SL-ST (Distant class)   | 9.49 | 11.92| 12.88|
| ST (Distant class)      | 2.34 | 3.81 | 4.62 |
| MAS (Distant class)     | 1.82 | 2.73 | 3.17 |
| MAS+ (Distant class)    | 1.47 | 2.01 | 2.10 |
Figure 6. Comparisons of transfer performance between sequential training (ST), sequential training with MAS (ST w/MAS), sequential training with MAS and reply (ST w/MAS+), and joint training (JT) for self-supervised pre-training with the distant class incremental sequence. On the right, we show the average performance for the two downstream tasks across all the datasets together with results of joint supervised pre-training (SL-ST) and sequential supervised pre-training (SL-ST).

Figure 7. Comparisons of transfer performance between sequential training (ST) and joint training (JT) for self-supervised pre-training with the domain incremental sequence. On the right, we show the average performance across all the datasets.

4.3. Resource efficiency

We then discuss the time and memory consumption of different training methods of SSL, including sequential training (ST), ST with MAS (MAS), ST with MAS and data replay (MAS+), and joint training (JT). As shown in Table 2, JT is very time-consuming especially when data amount is large, while ST is able to save a large amount of time under sequential training scenarios. To be specific, ST is about 2x faster than JT when there are 2 batches of data, and is about 4x faster when the batches number is 4. Moreover, when we use MAS and data replay to improve the performance of ST, the time consumption of SSL increases a little but is still significantly faster than JT. As for storage consumption, we can observe a similar phenomenon as shown in Table 2. In summary, sequential SSL pre-training is much more time-efficient and storage-saving than JT, especially when the data amount is large and grows quickly. Such a result suggests that sequential SSL is a more favorable choice for real-world applications, where data come in sequentially and grow daily.

Table 2. Time (h) and storage (GB) consumption of different methods regarding each data batch in the distant class incremental sequence of ImageNet. A lower value indicates a better efficiency.

| Time (Storage) | 1    | 2    | 3    | 4    |
|----------------|------|------|------|------|
| ST             | 16.69 (35) | 16.51 (35) | 16.54 (35) | 16.59 (35) |
| MAS            | 16.69 (35) | 18.20 (35) | 18.07 (35) | 18.05 (35) |
| MAS+           | 16.69 (35) | 22.37 (39) | 24.41 (42) | 26.43 (46) |
| JT             | 16.69 (35) | 31.08 (70) | 46.54 (105) | 66.62 (140) |

4.4. Features analysis

The above evaluation results have shown that SSL has a slight transfer performance gap between sequential training and joint training. To further understand sequential SSL, we analyze features in the sequential training process via Centered Kernel Alignment (CKA) [23]. CKA is usually used to measure the similarity between two representations of the same data samples. See Appendix F for details of the CKA similarity.
How features shift in sequential training? We first study how learned features shift in the process of sequential training via the CKA analysis on features. Specifically, we randomly sample 5,000 images from the first data batch in the sequence. We first extract the initial features of these data from the model trained with the first data batch. Starting from the second batch, at each data batch, we compute the CKA similarity between the initial features of sampled data and the features extracted from the model sequentially trained with the current data batch. Take Figure 8(a) as an example, when the current batch is 2, the CKA similarity of the sequential supervised model is about 0.8, which means after sequential training with the second data batch, the similarity between current features of sampled data and the initial features is 0.8.

We report results under three sequential training settings in Figure 8(a-c). We find SSL always has higher feature similarity than SL. This suggests that features of SSL shift less than features of SL during sequential training, leading to less knowledge forgetting. Moreover, for the distant class incremental sequence, equipped with the MAS regularization and data replay, sequential SSL features are almost the same as the initial features with a CKA similarity over 0.9. Such a result shows that with these two simple techniques, the model continually trained by SSL exhibits almost no features shift during the sequential training.

Sequential training vs. Joint training. We then evaluate CKA similarity between features from the jointly trained model and features from the sequentially trained model for each data batch. For example, as shown in Figure 8(d), at the second data batch, we compute the CKA similarity between features of the sampled data from the model jointly trained with the first two data batches and features from the model sequentially trained with the second data batch. The corresponding CKA similarity value is 0.4, which means for SL, the difference between joint training and sequential training is very large. In contrast, SSL has a higher similarity between sequential learning and joint training. Particularly, with MAS and data replay, the model trained by sequential SSL extracts nearly the same features as the jointly trained model. This illustrates that, even for the challenging distant class incremental sequence, one can also replace the joint training by the efficient sequential SSL pre-training.

5. Discussions

In this paper, we have conducted the first thorough empirical evaluation to investigate how well self-supervised learning (SSL) performs under sequential training scenarios. Our results show two main findings as follows:

Sequential self-supervised pre-training shows a better capability of overcoming catastrophic forgetting than supervised pre-training. One reason is that the features learned by contrastive SSL have been shown to be uniformly distributed over the feature space [56], which means the learned representations shift less during sequential training, as demonstrated by Section 4.4. In addition, features learned by the self-supervised task of instance discrimination are able to keep more visual information than the features learned by supervised pre-training [64], which weakens the effect of knowledge forgetting during sequential training.

Joint training is not necessary for SSL, while sequential training with suitable strategies is a good alternative. In the scenarios where distribution shifts within streaming data are mild (e.g., instance and random class incremental sequence), it is more favorable to directly conduct sequential SSL training that is far more efficient with negligible performance loss. On the other hand, if distribution shifts between streaming data are large, sequential SSL training with MAS+ is well worth considering.

Future directions. We first call for more attention to sequential self-supervised learning for understanding its underlying theories and devising better approaches. Also, we recommend considering sequential self-supervised training as a more efficient representation learning practice for real-world applications. Moreover, we will further investigate different self-supervised learning methods on various network architectures under sequential pre-training.
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References

[1] Rahaf Aljundi, Francesca Babiloni, Mohamed Elhoseiny, Marcus Rohrbach, and Tinne Tuytelaars. Memory aware synapses: Learning what (not) to forget. In European Conference on Computer Vision, 2018. 2, 3, 6, 12, 13
[2] Rahaf Aljundi, Klaas Kelchtermans, and Tinne Tuytelaars. Task-free continual learning. In Computer Vision and Pattern Recognition, 2019. 3, 13
[3] Thomas Berg, Jiongxin Liu, Seung Woo Lee, Michelle L Alexander, David W Jacobs, and Peter N Bellhumeur. Birdsnap: Large-scale fine-grained visual categorization of birds. In Computer Vision and Pattern Recognition, 2014. 5
[4] Lukas Bossard, Matthieu Guillaumin, and Luc Van Gool. Food-101 – mining discriminative components with random forests. In European Conference on Computer Vision, 2014. 5
[5] Mathilde Caron, Piotr Bojanowski, Armand Joulin, and Matthijs Douze. Deep clustering for unsupervised learning of visual features. In European Conference on Computer Vision, 2018. 1, 2
[6] Mathilde Caron, Ishan Misra, Julien Mairal, Priya Goyal, Piotr Bojanowski, and Armand Joulin. Unsupervised learning of visual features by contrasting cluster assignments. In Advances in Neural Information Processing Systems, 2020. 1, 4
[7] Ting Chen, Simon Kornblith, Mohammad Norouzi, and Geoffrey Hinton. A simple framework for contrastive learning of visual representations. In International Conference on Machine Learning, 2020. 2, 5
[8] Ting Chen, Simon Kornblith, Kevin Swersky, Mohammad Norouzi, and Geoffrey Hinton. Big self-supervised models are strong semi-supervised learners. In Advances in Neural Information Processing Systems, 2020. 2, 4
[9] Xinlei Chen, Haoqi Fan, Ross Girshick, and Kaiming He. Improved baselines with momentum contrastive learning. arXiv, 2020. 2, 3, 5, 12
[10] Mircea Cimpoi, Subhransu Maji, Iasonas Kokkinos, Sammy Mohamed, and Andrea Vedaldi. Describing textures in the wild. In Computer Vision and Pattern Recognition, 2014. 5
[11] Matthias Delange, Rahaf Aljundi, Marc Masana, Sarah Parisot, Xu Jia, Ales Leonardis, Greg Slabaugh, and Tinne Tuytelaars. A continual learning survey: Defying forgetting in classification tasks. IEEE Transactions on Pattern Analysis and Machine Intelligence, 2021. 2
[12] Jeff Donahue, Yangqing Jia, Oriol Vinyals, Judy Hoffman, Ning Zhang, Eric Tzeng, and Trevor Darrell. Decaf: A deep convolutional activation feature for generic visual recognition. In International Conference on Machine Learning, 2014. 1
[13] Linus Ericsson, Henry Gouk, and Timothy M Hospedales. How well do self-supervised models transfer? In Computer Vision and Pattern Recognition, 2021. 2, 4, 5
[14] Mark Everingham, Luc Van Gool, Christopher KI Williams, John Winn, and Andrew Zisserman. The pascal visual object classes (voc) challenge. International Journal of Computer Vision, 2010. 2, 5
[15] Li Fei-Fei, Rob Fergus, and Pietro Perona. Learning generative visual models from few training examples: An incremental bayesian approach tested on 101 object categories. In Computer Vision and Pattern Recognition Workshop, 2004. 5
[16] Spyros Gidaris, Praveer Singh, and Nikos Komodakis. Unsupervised representation learning by predicting image rotations. International Conference on Learning Representations, 2018. 1, 2
[17] Ian J Goodfellow, Mehdi Mirza, Da Xiao, Aaron Courville, and Yoshua Bengio. An empirical investigation of catastrophic forgetting in gradient-based neural networks. arXiv, 2013. 2, 12
[18] Jean-Bastien Grill, Florian Strub, Florent Altché, Corentin Tallec, Pierre H Richemond, Elena Buchatskaya, Carl Doersch, Bernardo Avila Pires, Zhaohan Daniel Guo, Mohammad Gheshlaghi Azar, et al. Bootstrap your own latent: A new approach to self-supervised learning. In Advances in Neural Information Processing Systems, 2020. 1, 2, 4
[19] Kaiming He, Haoqi Fan, Yuxin Wu, Saining Xie, and Ross Girshick. Momentum contrast for unsupervised visual representation learning. In Computer Vision and Pattern Recognition, 2020. 1, 2, 4, 5
[20] Kaiming He, Xiangyu Zhang, Shaoqing Ren, and Jian Sun. Deep residual learning for image recognition. In Computer Vision and Pattern Recognition, 2016. 2, 5
[21] Minyoung Huh, Pulkit Agrawal, and Alexei A Efros. What makes imagenet good for transfer learning? arXiv, 2016. 4, 13
[22] James Kirkpatrick, Razvan Pascanu, Neil Rabinowitz, Joel Veness, Guillaume Desjardins, Andrei A Rusu, Kieran Milan, John Quan, Tiago Ramalho, Agnieszka Grabska-Barwinska, et al. Overcoming catastrophic forgetting in neural networks. Proceedings of the National Academy of Sciences, 2017. 2, 3, 12
[23] Simon Kornblith, Mohammad Norouzi, Honglak Lee, and Geoffrey Hinton. Similarity of neural network representations revisited. In International Conference on Machine Learning, 2019. 7, 15
[24] Simon Kornblith, Jonathon Shlens, and Quoc V Le. Do better imagenet models transfer better? In Computer Vision and Pattern Recognition, 2019. 2
[25] Jonathan Krause, Jia Deng, Michael Stark, and Li Fei-Fei. Collecting a large-scale dataset of fine-grained cars. In Workshop on Fine-Grained Visual Categorization, 2013. 5
[26] Alex Krizhevsky, Geoffrey Hinton, et al. Learning multiple layers of features from tiny images. Master's thesis, University of Tornt, 2009. 5
[27] Alex Krizhevsky, Ilya Sutskever, and Geoffrey E Hinton. Imagenet classification with deep convolutional neural networks. In Advances in Neural Information Processing Systems, 2012. 2
[28] Gustav Larsson, Michael Maire, and Gregory Shakhnarovich. Learning representations for automatic colorization. In *European conference on computer vision*, 2016. 2

[29] Xuhong Li, Yves Grandvalet, and Franck Davoine. Explicit inductive bias for transfer learning with convolutional networks. In *International Conference on Machine Learning*, 2018. 2

[30] Xingjian Li, Haoyi Xiong, et al. Delta: Deep learning transfer using feature map with attention for convolutional networks. In *International Conference on Learning Representations*, 2019. 2

[31] David Lopez-Paz and Marc’Aurelio Ranzato. Gradient episodic memory for continual learning. In *Advances in Neural Information Processing Systems*, 2017. 3

[32] Dhruv Mahajan, Ross Girshick, Vignesh Ramanathan, Kaiming He, Manohar Paluri, Yixuan Li, Ashwin Bharambe, and Laurens Van Der Maaten. Exploring the limits of weakly supervised pretraining. In *European Conference on Computer Vision*, 2018. 2

[33] Subhransu Maji, Esa Rahtu, Juho Kannala, Matthew Blaschko, and Andrea Vedaldi. Fine-grained visual classification of aircraft. *arXiv*, 2013. 5

[34] Arun Mallya and Svetlana Lazebnik. Packnet: Adding multiple tasks to a single network by iterative pruning. In *Computer Vision and Pattern Recognition*, 2018. 3

[35] Michael McCloskey and Neal J Cohen. Catastrophic interference in connectionist networks: The sequential learning problem. In *Psychology of Learning and Motivation*. 1989. 2, 12

[36] George A Miller. *WordNet: An electronic lexical database*. MIT press, 1998. 4, 13

[37] Ishan Misra and Laurens van der Maaten. Self-supervised learning of pretext-invariant representations. In *Computer Vision and Pattern Recognition*, 2020. 2

[38] Behnam Neyshabur, Hanie Sedghi, and Chiyuan Zhang. What is being transferred in transfer learning? In *Advances in Neural Information Processing Systems*, 2020. 6

[39] Maria-Elena Nilsback and Andrew Zisserman. Automated classification of aircraft. *arXiv*, 2013. 5

[40] Mehdi Noroozi and Paolo Favaro. Unsupervised learning of visual representations by solving jigsaw puzzles. In *European Conference on Computer Vision*, 2016. 1, 2

[41] Aaron van den Oord, Yazhe Li, and Oriol Vinyals. Representation learning with contrastive predictive coding. *arXiv*, 2018. 2, 12

[42] German I Parisi, Ronald Kemker, Jose L Part, Christopher Kanan, and Stefan Wermter. Continual lifelong learning with neural networks: A review. *Neural Networks*, 2019. 3

[43] Omkar M Parkhi, Andrea Vedaldi, Andrew Zisserman, and CV Jawahar. Cats and dogs. In *Computer Vision and Pattern Recognition*, 2012. 5

[44] Xingchao Peng, Qinxun Bai, Xide Xia, Zijun Huang, Kate Saenko, and Bo Wang. Moment matching for multi-source domain adaptation. In *International Conference on Computer Vision*, 2019. 6, 13, 14

[45] Dushyant Rao, Francesco Visin, Andrei Rusu, Razvan Pascanu, Yee Whye Teh, and Raia Hadsell. Continual unsupervised representation learning. *Advances in Neural Information Processing Systems*, 2019. 3

[46] Sylvester-Alvise Rebuffi, Alexander Kolesnikov, Georg Sperl, and Christoph H Lampert. icarl: Incremental classifier and representation learning. In *Computer Vision and Pattern Recognition*, 2017. 3, 12

[47] Shaoqing Ren, Kaiming He, Ross Girshick, and Jian Sun. Faster r-cnn: Towards real-time object detection with region proposal networks. *arXiv*, 2015. 4

[48] David Rolnick, Arun Ahuja, Jonathan Schwarz, Timothy Lillicrap, and Gregory Wayne. Experience replay for continual learning. In *Advances in Neural Information Processing Systems*, 2019. 3, 12

[49] Olga Russakovsky, Jia Deng, Hao Su, Jonathan Krause, Sanjeev Satheesh, Sean Ma, Zhiheng Huang, Andrej Karpathy, Aditya Khosla, Michael Bernstein, et al. Imagenet large scale visual recognition challenge. *International Journal of Computer Vision*, 2015. 1, 4, 12

[50] Kuniaki Saito, Donghyun Kim, Stan Sclaroff, Trevor Darrell, and Kate Saenko. Semi-supervised domain adaptation via minimax entropy. In *Proceedings of the IEEE International Conference on Computer Vision*, 2019. 4, 14

[51] Joan Serra, Didac Suris, Marius Miron, and Alexandros Karatzoglou. Overcoming catastrophic forgetting with hard attention to the task. In *International Conference on Machine Learning*, 2018. 3

[52] Bart Thomee, David A Shamma, Gerald Friedland, Benjamin Elizalde, Karl Ni, Douglas Poland, Damian Borth, and Li-Jia Li. Yfccc100m: The new data in multimedia research. *Communications of the ACM*, 2016. 2

[53] Yonglong Tian, Dilip Krishnan, and Phillip Isola. Contrastive multiview coding. *arXiv*, 2019. 2

[54] Yonglong Tian, Chen Sun, Ben Poole, Dilip Krishnan, Cordelia Schmid, and Phillip Isola. What makes for good views for contrastive learning. In *International Conference on Learning Representations*, 2020. 2

[55] Liyuan Wang, Kuo Yang, Chongxuan Li, Lanqing Hong, Zhenguo Li, and Jun Zhu. Ordisco: Effective and efficient usage of incremental unlabeled data for semi-supervised continual learning. In *Computer Vision and Pattern Recognition*, 2019. 3

[56] Tongzhou Wang and Phillip Isola. Understanding contrastive representation learning through alignment and uniformity on the hypersphere. In *International Conference on Machine Learning*, 2020. 8

[57] Zhirong Wu, Yuanjun Xiong, Stella X Yu, and Dahua Lin. Unsupervised feature learning via non-parametric instance discrimination. In *Computer Vision and Pattern Recognition*, 2018. 2

[58] Jianxiong Xiao, James Hays, Krista A Ehinger, Aude Oliva, and Antonio Torralba. Sun database: Large-scale scene recognition from abbey to zoo. In *Computer Vision and Pattern Recognition*, 2010. 5
[59] Enze Xie, Jian Ding, Wenhai Wang, Xiaohang Zhan, Hang Xu, Zhenguo Li, and Ping Luo. Detco: Unsupervised contrastive learning for object detection. arXiv, 2021. 2

[60] Jason Yosinski, Jeff Clune, Yoshua Bengio, and Hod Lipson. How transferable are features in deep neural networks? In Advances in Neural Information Processing Systems, 2014. 13

[61] Matthew D Zeiler and Rob Fergus. Visualizing and understanding convolutional networks. In European Conference on Computer Vision, 2014. 1

[62] Friedemann Zenke, Ben Poole, and Surya Ganguli. Continual learning through synaptic intelligence. Proceedings of Machine Learning Research, 2017. 3

[63] Yifan Zhang, Bryan Hooi, Dupeng Hu, Jian Liang, and Jiashi Feng. Unleashing the power of contrastive self-supervised visual models via contrast-regularized fine-tuning. arXiv, 2021. 2

[64] Nanxuan Zhao, Zhirong Wu, Rynson WH Lau, and Stephen Lin. What makes instance discrimination good for transfer learning? In International Conference on Learning Representations, 2020. 8
Appendix

A. MoCo-v2

For the illustration purpose, we adopt a prevailing self-supervised learning (SSL) method, MoCo-v2 [9], to investigate the performance of SSL with streaming data. MoCo-v2 uses a Siamese network consisting of two encoders. These two encoders are designed for query images and key images, respectively, and share the same architecture where an MLP projection head \( f_w \) is on top of a backbone network \( f_\theta \). Only the query encoder is updated by the gradients backpropagation while the key encoder is updated by the moving average with a momentum. MoCo-v2 maintains an additional dictionary as a queue of features for contrastive learning. Specifically, features in the dictionary are progressively updated. The current mini-batch features from the key encoder are enqueued and the same number of oldest features are dequeued. MoCo-v2 uses InfoNCE [41], a variant of contrastive loss (CL), to maximize the similarity of features from positive pairs and minimize the similarity of features from negative pairs. The contrastive loss is formalized as below.

\[
L_{\text{cl}} = -\frac{1}{N} \sum_{i=1}^{N} \log \frac{e^{(z_i^T z_i^+ / \tau)}}{e^{(z_i^T z_i^+ / \tau)} + \sum_{z_j^- \in Z^-} e^{(z_i^T z_j^- / \tau)}},
\]

where \( N \) is the number of samples, \( z_i \) is the L2-normalized projected feature from the query encoder, \( z_i^+ \) is the L2-normalized projected feature of the same input image from the key encoder, \( Z^- \) are the negative history features stored in the dictionary and \( \tau \) is the temperature.

B. Data Replay and MAS

Continual learning is assumed to suffer from catastrophic forgetting of previously learned knowledge in supervised learning [17, 22, 35], leading to significant performance degradation of previous tasks. Here we introduce the continual learning techniques we adopt, including data replay [48, 46] and regularization-based method e.g. Memory Aware Synapses (MAS) [1].

Data replay. Data relay is a simple yet effective method for alleviating the catastrophic forgetting problem during the continual learning process. Specifically, we need to maintain a replay buffer and store a selected subset of samples from each learned task in the buffer. Then we just retrain on samples in the replay buffer to revisit old tasks while training the model for a new task.

MAS. Regularization-based methods aim to mitigate the catastrophic forgetting by consolidating previous knowledge with an added regularization term in the loss function. One typical unsupervised regularization-based method is MAS [1]. Specifically, MAS proposes to compute gradients the squared L2-norm of the encoder output \( f_\theta \) as the importance weights of parameters.

\[
\Omega_{ij} = \frac{1}{N} \sum_{k=1}^{N} \frac{\partial [\|f_\theta(x)\|_2^2]}{\partial \theta_{ij}}.
\]

With the parameter regularization term added, the resulting loss function with the coefficient \( \lambda \) is shown as below.

\[
\mathcal{L}(\theta) = \mathcal{L}_{\text{cl}}(\theta) + \lambda \sum_{i,j} \Omega_{ij} (\theta_{ij} - \theta_{ij}^*)^2.
\]

C. Streaming Data

We consider four kinds of streaming data for study, i.e., the instance incremental sequence, the random class incremental sequence, the distant class incremental sequence, and the domain incremental sequence. To exclude the effect of the number of images, we make sure that data batches in the same sequence have almost the same data amount. Here we provide more details about these data sequences.

```
Figure 9. The number of classes for each connected component from the adjacent matrix of 1,000 classes in ImageNet.
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Table 3. The statistics for the four data batches in the distant class incremental sequence.

|      | 1   | 2   | 3   | 4   |
|------|-----|-----|-----|-----|
| Classes | 250 | 250 | 251 | 249 |
| Images  | 318,459 | 321,488 | 321,533 | 319,687 |

Instance incremental sequence. For the instance incremental sequence, we split the ImageNet [49] training data that consists of 1.28 million images with 1,000 classes into
four even batches. We ensure that each data batch includes the same 1,000 classes with the same number of images for each class, which means these data batches are independent and identically distributed (IID).

**Random class incremental sequence.** For the random class incremental sequence, we randomly split the 1,000 classes of ImageNet into four parts where each part has 250 classes. Since each class of ImageNet has around 1,000 images, we can directly obtain four data batches with almost the same amount of images.

**Distant class incremental sequence.** To explore the data sequence with large distribution shifts among data batches, we consider the distant class incremental sequence. Following [60, 21], rather than randomly splitting the 1,000 classes, we leverage the WordNet Tree [36] to obtain four even data batches sharing the minimal semantic overlapping. We first build a 1000*1000 adjacent matrix among the 1,000 classes by setting the value of similar classes as 1 and the value of dissimilar classes as 0. To be specific, we take classes sharing the common parent node beneath the ninth depth in the WordNet Tree as similar classes and vice versa. Using the semantic similarity described in the adjacent matrix, we then split the 1,000 classes into independent connected components as shown in Figure 9. Finally, we merge these imbalanced components into four almost even data batches as shown in Table 3.

![Figure 10. Example images in the five domains of DomainNet.](image)

**Domain incremental sequence.** As for the domain incremental sequence, we consider a multi-domain dataset called DomainNet [44]. In our work, we adopt a domain incremental data sequence made of four distant domains including ‘sketch’, ‘real’, ‘painting’ and ‘clipart’. Although there exist large domain distribution shifts among these four domains, we observe that sequential self-supervised pre-training shows almost the same transfer performance as the joint self-supervised pre-training. To further study the multi-domain sequential pre-training, we build another domain incremental data sequence with five domains. Specifically, we add a new domain called ‘quickdraw’, where images mostly contain only lines without visual textures. As a result, images from ‘quickdraw’ are less informative and more visually distinct, compared with images from those four domains, as shown in Figure 10. For each domain, we randomly select 48,129 images as a data batch, except for ‘quickdraw’ where we select 47,687 images.

**E. More Experiments on DomainNet**

For the domain incremental sequence, we first consider a four-domain sequence including ‘clipart’, ‘painting’, ‘real’ and ‘sketch’. As shown in Figure 7, sequential self-supervised pre-training shows comparable if not better transfer performance, compared with joint self-supervised pre-training. Observations from four-domain experiments denote that sequential self-supervised pre-training can have competitive transfer performance on streaming data with large domain distributions shifts.

To further evaluate how well self-supervised per-training performs on streaming data with larger domain distribution shifts, we then consider a five-domain sequence by adding
Figure 11. The average few-shot transfer performance across five sequences between sequential training (ST) and joint training (JT) for self-supervised pre-training with domain incremental streaming data. On the right, we show the average performance across all the datasets.

Figure 12. The few-shot transfer performance of the five-domain sequence ‘clipart → painting → quickdraw → real → sketch’ between sequential training (ST) and joint training (JT) for self-supervised pre-training with domain incremental streaming data. On the right, we show the average performance across all the datasets.

Figure 13. The few-shot transfer performance of the five-domain sequence ‘painting → quickdraw → real → sketch → clipart’ between sequential training (ST) and joint training (JT) for self-supervised pre-training with domain incremental streaming data. On the right, we show the average performance across all the datasets.

Figure 14. The few-shot transfer performance of the five-domain sequence ‘quickdraw → real → sketch → clipart → painting’ between sequential training (ST) and joint training (JT) for self-supervised pre-training with domain incremental streaming data. On the right, we show the average performance across all the datasets.

Figure 15. The average few-shot transfer accuracy (% of batches) for aircrafts, caltech, flowers, pets, cars, DTD, CIFAR10, CIFAR100, birds, and Sun397 datasets.

Figure 16. The average few-shot transfer accuracy (% of batches) for aircrafts, caltech, flowers, pets, cars, DTD, CIFAR10, CIFAR100, birds, and Sun397 datasets.

Figure 17. The average few-shot transfer accuracy (% of batches) for aircrafts, caltech, flowers, pets, cars, DTD, CIFAR10, CIFAR100, birds, and Sun397 datasets.

Figure 18. The average few-shot transfer accuracy (% of batches) for aircrafts, caltech, flowers, pets, cars, DTD, CIFAR10, CIFAR100, birds, and Sun397 datasets.

Figure 19. The average few-shot transfer accuracy (% of batches) for aircrafts, caltech, flowers, pets, cars, DTD, CIFAR10, CIFAR100, birds, and Sun397 datasets.

Figure 20. The average few-shot transfer accuracy (% of batches) for aircrafts, caltech, flowers, pets, cars, DTD, CIFAR10, CIFAR100, birds, and Sun397 datasets.

Figure 21. The average few-shot transfer accuracy (% of batches) for aircrafts, caltech, flowers, pets, cars, DTD, CIFAR10, CIFAR100, birds, and Sun397 datasets.

Figure 22. The average few-shot transfer accuracy (% of batches) for aircrafts, caltech, flowers, pets, cars, DTD, CIFAR10, CIFAR100, birds, and Sun397 datasets.

Figure 23. The average few-shot transfer accuracy (% of batches) for aircrafts, caltech, flowers, pets, cars, DTD, CIFAR10, CIFAR100, birds, and Sun397 datasets.

Figure 24. The average few-shot transfer accuracy (% of batches) for aircrafts, caltech, flowers, pets, cars, DTD, CIFAR10, CIFAR100, birds, and Sun397 datasets.

Figure 25. The average few-shot transfer accuracy (% of batches) for aircrafts, caltech, flowers, pets, cars, DTD, CIFAR10, CIFAR100, birds, and Sun397 datasets.

Figure 26. The average few-shot transfer accuracy (% of batches) for aircrafts, caltech, flowers, pets, cars, DTD, CIFAR10, CIFAR100, birds, and Sun397 datasets.

an extra domain ‘quickdraw’. Note that ‘quickdraw’ is quite visually different from other domains in DomainNet and domain adaptation results from other domains to ‘quickdraw’ are especially low [44]. Besides, the prevailing domain adaptation work [50] considers the same four domains as our four-domain sequence.

The few-shot evaluation results averaged across five sequences are shown in Figure 11. For most datasets, sequential self-supervised learning (SSL) shows an obvious transfer performance gap to joint self-supervised pre-training.
Results averaged across 11 datasets further demonstrate that for this five-domain data sequence, sequential SSL performs obviously worse than joint SSL. For more comprehensive comparisons between sequential training and joint training on the five-domain incremental data sequence, we report transfer results of five data sequences obtained by right circular shift operations over the default data sequence ‘clipart → painting → quickdraw → real → sketch’. To be specific, results of ‘clipart → painting → quickdraw → real → sketch’ are in Figure 12, results of ‘painting → quickdraw → real → sketch → clipart’ are in Figure 13, results of ‘quickdraw → real → sketch → clipart → painting’ are in Figure 14, results of ‘real → sketch → clipart → painting → quickdraw’ are in Figure 15 and results of ‘sketch → clipart → painting → quickdraw → real’ are in Figure 16.

From results of five sequences, we have the following observations. As for the average transfer performance across all downstream datasets, sequential training shows an obvious gap to joint training, while the efficient 10% data replay strategy can effectively mitigate the performance gap. Take a close look at intermediate transfer results of each data batch, we find that ‘quickdraw’ leads to the largest transfer performance drop during the sequential training process across all five data sequences. In addition, ‘sketch’ causes the obvious performance drop in the sequence ‘real → sketch → clipart → painting → quickdraw’, as shown in Figure 15. Such results suggest that sequential SSL may also suffer from obvious forgetting of previous knowledge when there exist large distribution shifts within streaming data. Generally, sequential SSL on streaming data with large distribution shifts may suffer from an non-negligible transfer performance gap to joint SSL. However, such performance gap can be mitigated effectively and efficiently with simple continual learning techniques such as the data replay and the parameter regularization.

F. Details on CKA Similarity

To further understand the sequential self-supervised pre-training, we then take a closer look at the learned feature representations during the sequential training process. We leverage the linear centered kernel alignment (CKA) [23] to measure the similarity of output features between two different representation networks given the same data set as input. If we consider the size of the data set as $n$ and the feature dimension for two networks as $d_1$ and $d_2$, respectively. We use the selected data set to extract features $X \in \mathbb{R}^{n \times d_1}$ from one representation network and features $Y \in \mathbb{R}^{n \times d_2}$ from another representation network. In our experiments, $n$ is 50,000 and both $d_1$ and $d_2$ are 2,048. We first preprocess the two representation matrices by centering the columns. Then the linear CKA similarity between two representations $X$ and $Y$ can be computed as below.

$$CKA(X, Y) = \frac{\|X^T Y\|_F^2}{\|X^T X\|_F \|Y^T Y\|_F}$$
G. Downstream Hyper-Parameters.

We perform no hyper-parameter tuning for few-shot evaluation and detection evaluation. As for many-shot evaluation, we adopt the logistic regression and only tune the weight decay value. The inversed weight decay values for all downstream classification datasets are given in Table 4.

Table 4. The inverse of regularization strength (weight decay value) used in many-shot logistic regression evaluation on 12 different downstream classification datasets. SSL models: self-supervised models. SL models: supervised models.

| Dataset     | SSL Models   | SL Models   |
|-------------|--------------|-------------|
| Aircraft    | 5623.413277133687 | 9.99999985098839 |
| Caltech-101 | 316227.77125655657 | 0.3162277621819913 |
| Flowers     | 31622.77530666721 | 999.999952502551 |
| Pets        | 999.999952502551 | 562.3413185099295 |
| Cars        | 5623.413277133687 | 17.782794106882072 |
| DTD         | 1778.2794843157246 | 0.0177827946252197 |
| Food        | 177827.94843157247 | 0.0562341298247638 |
| CIFAR10     | 316227.77125655657 | 0.0562341298247638 |
| CIFAR100    | 100.00000223517424 | 0.0562341298247638 |
| Birdsnap    | 1778.2794843157246 | 0.1 |
| SUN397      | 100.00000223517424 | 0.0177827946252197 |
| VOC2007     | 9.99999985098839  | 0.005623413223739 |