Self-Supervised Learning for pre-training models in Computer Vision

Continual Learning Report

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Contents

Abstract

In this work some self-supervised learning methods for computer vision will be explored. In the first part the general framework of self-supervised learning will be discussed, describing all the aspects which are in common to the methods that will be explained. After that five different self-supervised learning methods will be described in detail and in the final part of the work those methods will be compared, both in term of performances and in the way they address some specific problems, exposing strengths and weaknesses of each method.

1 Introduction

Self-Supervised Learning (SSL) is a particular machine learning technique that enables models to learn from unlabeled data by self-generating the labels from the input patterns, usually requiring the model to predict or reconstruct some aspect of the input. The main objective of SSL is to pre-train a model on a large dataset using these self-generated labels, which allows the model to learn a meaningful and useful representation of the input data. This pre-trained model can then be fine-tuned on downstream tasks with a smaller labeled datasets, hopefully leading to improved performance and faster convergence compared to training the model from scratch. By learning a useful representation of the input, the pre-trained model can extract relevant features and patterns that are beneficial for the downstream tasks, even if the labeled dataset is different from the original unlabeled dataset used for pre-training. SSL has the advantages of requiring less labeled data, which are usually hard to acquire, enabling to learn from unlabeled data, which are easier to get. Moreover the same pre-trained model might be used for many downstream tasks.
SSL gained a lot of popularity in the field of natural language process, where pre-training large language models on pretext tasks, such as masked language modeling or next word prediction, allowed to reach remarkable performances on many downstream tasks. In this work some techniques to perform SSL in computer vision scenarios will be analyzed, discussed and compared.

2 Problem setting

As explained in the previous section we will consider SSL for computer vision tasks. In general when we train a self-supervised model there are two main stages:

- **Pretext task**: which is the self-supervised task that is used to pre-train the model. The goal of this task is to learn a good intermediate representation with the expectation that this representation can carry good semantic or structural meanings and can be beneficial for many downstream tasks.
- **Downstream task**: which is the supervised task (such as image classification or object detection) on which we want to evaluate the model. In this stage the pre-trained model is used as a starting point, and the weights are adjusted through supervised training on the downstream task, using labeled data.

In general we don't care about the performances of the model in the pretext task, and we just care about the performances on the downstream tasks. When fine-tuning the model on the downstream task, usually a classifier (typically an MLP) is added at the end of the feature extractor learned during the pre-training, and it is trained to perform the supervised task. In general for the fine-tuning we can:

– Train the parameters of the whole architecture

– Freeze the parameters of the feature extractor and only train the weights of the MLP head

– Freeze the parameters of the first K layers of the feature extractor and train the weights of the rest of the architecture

Almost all the methods that we'll explore exploit two fundamental concepts for SSL in computer vision: data augmentation and contrastive learning. As we already said in SSL we want to train a model using unlabeled data to predict some properties of the data. In the textual domain this is usually done by masking some words in a sentence and training the model to predict those words. In computer vision one possible way of doing this is by taking an image, producing different views of that image by applying to each view a different set of transformations, and consider views produced from the same image to belong to the same class. We define a couple of images to be a positive pair if they are different views of the same image, on the contrary we define the couple as a negative pair if the two images are views from different images. Intuitively in the latent representation learned by the self-supervised model we would like positive pairs to be close and negative pairs to be far apart. In contrastive learning this intuition is made explicit in the loss function used to train the self-supervised model, so that minimizing the loss also minimizes the distance between positive images and maximizes the distance between negative images.

3 Methodology

In the following section the five considered self-supervised learning methods will be described in detail.

Contrastive Predicting Coding

Contrastive Predictive Coding (CPC) [1] is a method which has been thought actually not only for the computer vision field, but it can be applied also to other domains like audio and natural language. The idea of the method is to train a model that learns the representation of the data by predicting the representation of future observations from the past ones. When applied to image processing CPC works as follows: from an image we extract a certain number of overlapping crops of a fixed size and we organize those crops in a grid. If $x_{i,j}$ is the crop in position i, j of the grid, then we use an encoder $f_\theta(\cdot)$ to encode each crop of the grid into a single vector $z_{i,j} = f_\theta(x_{i,j})$. After that a second auto-regressive model $g_\phi(\cdot)$ is used to compute $c_{i,j} = g_\phi(\{z_{u,v}\}_{u \le i,v})$ that is a context vector that summarizes the feature in the previous rows but in the same column of $z_{i,j}$. The predictive tasks consists of predicting a feature vectors $z_{i+k,j}$ from the context vector $c_{i,j}$, where $k > 0$, using a linear model W_k computing $\hat{z}_{i+k,j} = W_k c_{i,j}$. To measure the quality of the prediction a contrastive loss is employed:

$$\mathcal{L}_{\text{CPC}} = -\sum_{i,j,k} \log p(z_{i+k,j}|\hat{z}_{i+k,j}, \{z_l\}) = -\sum_{i,j,k} \log \frac{\exp\left(\hat{z}_{i+k,j}^T z_{i+k,j}\right)}{\exp\left(\hat{z}_{i+k,j}^T z_{i+k,j}\right) + \sum_l \exp\left(\hat{z}_{i+k,j}^T z_l\right)}$$

where $\{z_l\}$ is the set of negative samples which is composed by taking crops from different location of the grid. In the paper they prove formally that minimizing this loss is equivalent of maximizing the mutual information between $c_{i,j}$ and $x_{i+k,j}$, obtaining the bound:

$$I(x_{i+k,j}, c_{i,j}) \geq \log(N) - \mathcal{L}_{CPC}$$

where N is the number of negative examples used in the loss. After having trained the whole architecture, for the fine-tuning on downstream tasks we keep only the encoder network $f_\theta(\cdot)$ and use it as feature extractor for a classification model, which is then trained on a supervised task. For the encoder f_θ any CNN can be applied, in the paper the authors used a ResNet101, while for the auto-regressive model g_ϕ they used a PixelCNN.

In [2] the authors proposes CPC-v2, an improved version of CPC where essentially they do some modification of some training details like applying augmentation to the crops individually, increasing the crops sizes, using layer normalization instead of batch normalization and some other minors modifications, but the backbone of the method remains the same.

Contrastive Multi-view Coding

In Contrastive Multi-view Coding (CMC) [3] the authors start from the framework proposed in CPC, but they adapt it to maximize the mutual information between different views of the same image, removing the prediction part and focusing on contrastive learning. Suppose we have two different views of a dataset V_1 and V_2, and we build a dataset that consist of a collection of samples $\{v_1^i, v_2^i\}_{i=1}^N$. We consider positive pairs those which are sampled from the joint distribution $x \sim p(v_1, v_2)$ where $x = \{v_1^i, v_2^i\}$, while we consider negative samples those sampled from the product of marginals $y \sim p(v_1)p(v_2)$ where $y = \{v_1^i, v_2^j\}$. The goal is to learn a critic function h_θ which is trained to output high values for positive pairs and low values for negative pairs. In this way we can use a contrastive loss function that we can use to train the model to correctly select a single positive sample out of a set that contains k negative samples:

$$\mathcal{L}_{contrast}^{V_1,V_2} = -\mathbb{E}_{\{v_1^1, v_2^1, \ldots, v_2^{k+1}\}}\left[\log \frac{h_\theta(\{v_1^1, v_2^1\})}{\sum_{j=1}^{k+1} h_\theta(\{v_1^1, v_2^j\})}\right]$$

where $\{v_1^1, v_2^1\}$ is the positive pair and $\{v_1^1, v_2^j\}$ with $j > 1$ is the a negative pair. To extract the latent representations of v_1 and v_2 we use two encoders $f_{\theta_1}(\cdot)$ and $f_{\theta_2}(\cdot)$. We compute the latent representations $z_1 = f_{\theta_1}(v_1)$ and $z_2 = f_{\theta_1}(v_2)$ which we can use to compute the output of the critic as:

$$h_\theta(\{v_1, v_2\}) = \exp\left(\frac{z_1^T z_2}{\|z_1\|\|z_2\|} \cdot \frac{1}{\tau}\right)$$

In the formulation of $\mathcal{L}^{V_1,V_2}_{contrast}$ the view V_1 is used as anchor view, while we enumerate samples from view V_2, but we can also do the opposite and use the following loss:

$$\mathcal{L}(V_1, V_2) = \mathcal{L}^{V_1,V_2}_{contrast} + \mathcal{L}^{V_2,V_1}_{contrast}$$

After the training phase, if we want for instance to fine-tune the model on an image classification task, we can concatenate the output of the two encoder networks f_{θ_1} and f_{θ_2} and use it as input of a classification network. In the paper the authors prove that the optimal critic h^*_θ is proportional to the density ratio between the joint distribution $p(z_1, z_2)$ and the product of the marginals $p(z_1)p(z_2)$:

$$h^*_\theta(\{v_1, v_2\}) \propto \frac{p(z_1, z_2)}{p(z_1)p(z_2)} \propto \frac{p(z_1|z_2)}{p(z_1)}$$

that is the point-wise mutual information and from this the same bound obtained for CPC can be derived:

$$I(z_i; z_j) \geq \log(k) - \mathcal{L}_{contrast}$$

hence minimizing the contrastive loss yields to the maximization of the mutual information between the latent representation of the different views.
Then the authors proposes two different ways for extending the this framework to the usage of multiple views. Suppose we have M different views of a dataset $V_1, \ldots, V_M$, we can extend CMC to the multiple views case using the following losses:

$$\mathcal{L}_C = \sum_{j=2}^{M} \mathcal{L}(V_1, V_j), \qquad \mathcal{L}_F = \sum_{j=1}^{M} \sum_{i=1}^{j-1} \mathcal{L}(V_i, V_j)$$

in the core view formulation ($\mathcal{L}_C$) we select one view that we want to optimize, for instance V_1, and we build a pairwise representations between V_1 and all the other views. In the full graph formulation ($\mathcal{L}_F$) we instead consider all the possible pairs. The full graph formulation is more computational expensive but it has the advantage that it allows to capture more information between different views.
In order to achieve good results using many negative examples in the contrastive loss, CMC uses a memory bank to store latent representations for each training sample, so that a certain amount of negative samples can be retrieved from the memory bank without recomputing the features each time. The drawback of course is the fact the representations in the memory becomes old after some time and they must be updated after some time.
In the experiments in order to produce different views of the images, they convert the images from the RGB to the Lab representation, and then they split each image into L and ab channels. Of course L and ab from the same image are considered positive pairs. They do the same thing for the YDbDr color space, splitting the Y and DbDr channels. For testing the multi-views case they again use the Lab representation separating the L and ab channels, and they also include other three views depth, surface normal and semantic labels (example in figure 1).

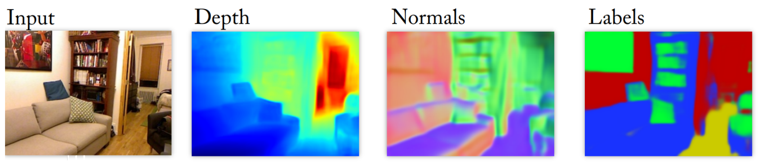


Figure 1: Example of depth, normal and semantic labels views of an image

Pre-text Invariant Representation Learning

Pre-text Invariant Representation Learning (PIRL) [4] is a SSL method that uses contrastive learning like CMC, but the intention of the author is to train a model which learns a representation of the input images that is invariant with respect to image transformations.

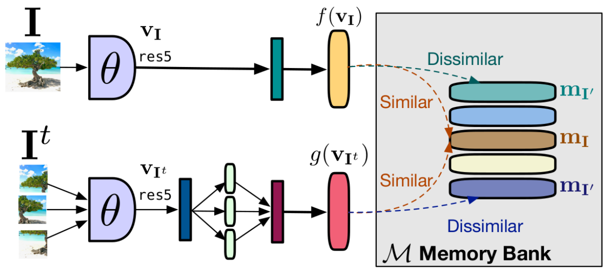


Figure 2: Scheme that shows how PIRL works

Given a dataset of images $\mathcal{D} = \{I_1, \ldots, I_{|D|}\}$ where $I_n \in \mathbb{R}^{H\times W\times 3}$ and set of transformation $\mathcal{T}$, the goal of PIRL is to train a convolutional neural network $\phi_\theta(\cdot)$ that constructs image representations $v_I = \phi_\theta(I)$ which are invariant to image transformations in $\mathcal{T}$. In order to do so ϕ_θ is trained to minimize the following loss function:

$$\ell_{inv}(\theta; \mathcal{D}) = \mathbb{E}_{t\sim p(\mathcal{T})}\left[\frac{1}{|D|}\sum_{I\in\mathcal{D}} L(v_I, v_{I^t})\right]$$

where $I^t = t(I)$ is the image I after transformation t, $L(\cdot,\cdot)$ measures the similarity between two image representations and $p(\mathcal{T})$ is a distribution over the transformation in $\mathcal{T}$. The minimization of this loss encourages the network $\phi_\theta(\cdot)$ to produce the same representation for the image I as the transformed counter part I^t, so to make the representation invariant with respect to transformation t. This is in contrast to other losses of the following form:

$$\ell_{cov}(\theta; \mathcal{D}) = \mathbb{E}_{t\sim p(\mathcal{T})}\left[\frac{1}{|D|}\sum_{I\in\mathcal{D}} L_{co}(v_I, z(t))\right]$$

where z is a function that measures some property of the transformation t. These kind of losses push the network $\phi_\theta(\cdot)$ to make the representation covariant with respect to the transformation, which causes the network to learn information that are not semantically relevant (like in the case of CMC). $L(\cdot,\cdot)$ is defined as a contrastive loss:

$$h(v_I, v_{I^t}) = \frac{\exp\Big(s(v_I, v_{I^t})/\tau\Big)}{\exp\Big(s(v_I, v_{I^t})/\tau\Big) + \sum_{I'\in\mathcal{D}_N}\exp\Big(s(v_I, v_{I'})/\tau\Big)}$$

where $\mathcal{D}_N \subseteq \mathcal{D}\setminus\{I\}$ is a set of negative samples and $s(\cdot,\cdot)$ is a similarity function. Actually to compute the similarity we do not compute the features v directly but we apply different heads. Specifically we use $f(\cdot)$ for v_I and $g(\cdot)$ for v_{I^t}. So the actual loss is:

$$L_{\text{NCE}}(I, I^t) = -\log\Big(h(f(v_I), g(v_{I^t}))\Big) - \sum_{I'\in\mathcal{D}_N}\log\Big(1 - h(g(v_I^t), f(v_{I'}))\Big)$$

which encourages the representation of image I to be similar to the one of its transformed counterpart I^t, while also encouraging it to be dissimilar to the representation of other images I'.
To address the problem of finding many negative samples during the training the authors decided to use a memory bank $\mathcal{M}$ that contains the feature representation m_I of image $I \in \mathcal{D}$. m_I is an exponential moving average of the feature representation $f(v_I)$ that were computed in the prior epochs. In this way we can replace in the loss definition the negative samples $f(v'_I)$ by their memory bank representation $m_{I'}$, while keeping the batch size small. All the representation that are stored in the memory bank are all computed on the original images, I, without the transformation t. An issue of L_{NCE} is that it does not compare the representation of the original image I with the representation of the negative samples I', and this is fixed by using the following loss instead:

$$L(I, I^t) = \lambda L_{\text{NCE}}(m_I, g(v_{I^t})) + (1 - \lambda) L_{\text{NCE}}(m_I, f(v_I))$$

where the first term is the one we had before and the second term encourages the representation of $f(v_I)$ to be similar to its memory bank representation m_I and it also encourages the representation of $f(v_I)$ and $f(v_{I'})$ to be dissimilar. For the experiments the authors used a ResNet to compute the representation of the images, while for the heads f and g they use two different linear layers. When we have to fine-tune the model on the downstream task we remove the heads and we only keep the encoder network ϕ_θ.

Momentum Contrast

Momentum Contrast (MoCo) [5] uses a prospective of contrastive learning as dictionary look-up. If we consider and encoded query q and a and encoded set of of keys of the dictionary $\{k_1, k_2, \dots\}$ and we assume that there exists a single key k_+ that matches with q, we can define a contrastive loss ass a function that is low when q is similar to its positive key k_+ and dissimilar to all the other negative keys. Specifically in the paper they use the InfoNCE loss:

$$\mathcal{L}_q = -\log\left(\frac{\exp\left(q^T k_+ / \tau\right)}{\sum_{i=0}^{K} \exp(q^T k_i / \tau)}\right)$$

that can be used as an unsupervised objective function for training the encoder networks that represent the queries and the keys: $q = f_q(x^q)$ and $k = f_k(x^k)$. Under this dictionary lookup prospective, contrastive learning is a way for building a discrete dictionary on high dimensional continuous inputs. This dictionary is dynamic since the keys are randomly sampled and $f_k(\cdot)$ changes during training. Instead of using a memory bank like the ones of CMC and PIRL, MoCo maintains a queue of mini-batches of data samples. In this way the encoded keys from the preceding mini-batches can be used in the loss: at each training step the current mini batch is inserted in the queue and the oldest mini-batches is removed from the queue. The problem of using a large queue as a dictionary can be the update of the key encoder using back propagation intractable, since the gradient should propagate to all the samples in the queue, so the authors solve this problem by updating f_k's parameters θ_k as a moving average of f_q's parameters θ_q:

$$\theta_k \leftarrow m\theta_k + (1 - m)\theta_q$$

where $m \in [0, 1)$. θ_q is normally updated using back-propagation. In this way θ_k evolves more smoothly than θ_q, so even if the keys in the queue are encoded by different encoders, the difference

between these encoders can be made small.
MoCo has been improved in a successive work [6] in which the authors applied to it some of the improvement proposed by SimCLR, which are a stronger data augmentation and the use of a MLP projection head after having computed the representation of the images using the encoder networks.

Swapping Assignments between Multiple Views

Swapping Assignments between Multiple Views (SWAV) [7] unlike all the other methods we've seen, it does not use contrastive learning but it is an online clustering based method. In clustering based method the idea is to use a clustering algorithm to cluster the embeddings of a batch of images, and use those embeddings as pseudo-label for a predictive task in which a model given the embedding of the images is trained to predict the cluster of each image. This method was proposed in Deep Cluster [8].

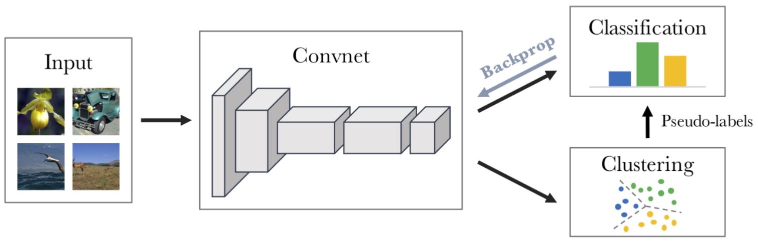


Figure 3: General framework of clustering based methods

With SWAV the authors combine the idea of contrastive learning, which is comparing different views of the images produced with augmentation, with a clustering based pretext task. SWAV works as follows: each image x_n is transformed into an augmented view x_{nt} by applying a transformation $t \sim \mathcal{T}$, where $\mathcal{T}$ is a set of augmentations. Then we map the augmented view to a vector representation with a non-linear mapping f_θ to x_{nt} and we then project this feature in a unit sphere $z_{nt} = f_\theta(x_{nt})/\|f_\theta(x_{nt})\|_2$. From this representation we compute the code q_{nt} by mapping z_{nt} to a set of K trainable prototypes vectors $\{c_1, \ldots, c_k\}$. We use C to denote the matrix whose columns are the $c_1, \ldots, c_k$ vectors. If we do the same thing with another augmentation $s \sim \mathcal{T}$, obtaining the image feature z_{ns} and its corresponding code q_{ns} then we can set a swapped prediction problem using the following loss:

$$L(z_{nt}, z_{ns}) = \ell(z_{nt}, q_{ns}) + \ell(z_{ns}, q_{nt})$$

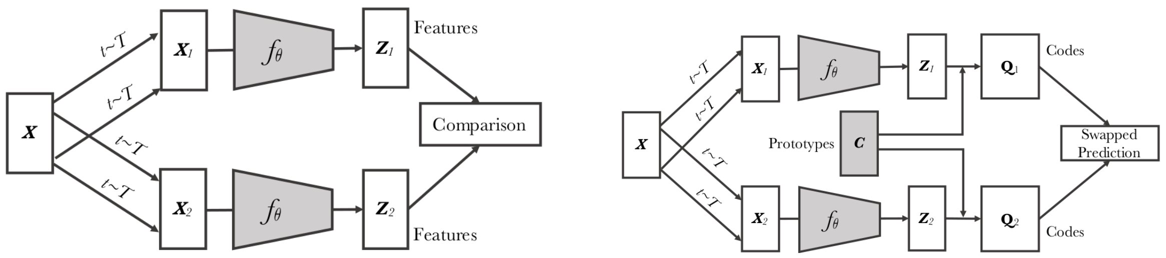
where the function $\ell(z, q)$ measures the fit between features z and the code q. The idea is that instead of comparing directly the features of z_t and z_s, we do it using the intermediate codes q_t and q_s. If these two features capture the same information, it should be possible to predict the code of the feature z_q using the feature z_t and vice versa. The loss $\ell(z_t, q_s)$ is the cross entropy loss between the code and the probability obtained by taking a soft-max of the dot product of x_i and all the prototypes in C:

$$\ell(z_t, q_s) = -\sum_k q_s^{(k)} \log p_t^{(k)}, \qquad p_t^{(k)} = \frac{\exp\left(z_t^T c_k/\tau\right)}{\sum_{k'} \exp(z_t^T c'_k/\tau)}$$

by applying some mathematical manipulations to these formula we can obtain our objective:

$$\frac{1}{N}\sum_{n=1}^{N}\sum_{s,t\sim\mathcal{T}} L(z_{nt}, z_{ns}) = -\frac{1}{N}\sum_{n=1}^{N}\sum_{s,t\sim\mathcal{T}}\left[\frac{1}{\tau}z_{nt}^{T}Cq_{ns}+\frac{1}{\tau}z_{ns}^{T}Cq_{nt}-\log\sum_{i=1}^{K}\exp\left(\frac{z_{nt}^{T}c_k}{\tau}\right)-\log\sum_{i=1}^{K}\exp\left(\frac{z_{ns}^{T}c_k}{\tau}\right)\right]$$

so we can train the parameters θ of the encoding function $f_\theta(\cdot)$ to minimize this loss.



(a) Contrastive learning framework

(b) SWAV framework

Figure 4: Difference between classical contrastive learning and SWAV

The question now is how do we compute the codes? Given a batch of B features $Z = [z_1, \ldots, z_B]$ we want to map them to the prototypes $C = [C_1, \ldots, C_K]$, obtaining the codes $Q = [q_1, \ldots, q_B]$, where Q is an $K \times B$ matrix where $Q_{i,j}$ can be viewed as the probability of feature z_j to belong to the prototype c_i. We want to optimize Q to maximize the similarity between features and prototypes, and this can be expressed in the following maximization problem:

$$\max_{Q\in\mathcal{Q}}\left\{\operatorname{Tr}\left(Q^T C^T Z\right) + \epsilon H(Q)\right\}$$

where $H(Q) = -\sum_i \sum_j Q_{i,j}\log Q_{i,j}$ and ϵ is a parameter that controls the smoothness of the mapping and the matrix $C^T Z$ contains the similarity of each feature vector and each prototype, since $(C^T Z)_{i,j} = c_i^T z_j$. While solving the problem we need to avoid the trivial solution in which all the features are mapped to the same code. This can be achieved by imposing an equipartition constraint, basically forcing the number of feature vectors which are mapped to a given prototype has to be more or less the same for all the prototypes. In order to enforce the equal partitioning constraint the set $\mathcal{Q}$ is defined as:

$$\mathcal{Q} = \{Q \in \mathbb{R}^{K\times B} | Q\mathbb{1}_B = \frac{1}{k}\mathbb{1}_k, Q^T\mathbb{1}_K = \frac{1}{B}\mathbb{1}_B\}$$

where $\mathbb{1}_K$ denotes the K-dimensional vector where all the elements are 1. The solution to the optimization problem can be computed as:

$$Q^* = \operatorname{Diag}(u)\exp\left(\frac{C^T Z}{\epsilon}\right)\operatorname{Diag}(v)$$

where u and v are re-normalization vectors in $\mathbb{R}^K$ and $\mathbb{R}^B$, which can be computed with the Sinkhorn-Knopp algorithm.

4 Analysis and comparison

In this section the five methods we have explained will be compared in term of performances on different downstream tasks. In addition two other methods which have been explored during the lectures will be considered, SimCLR [6] and BYOL [9]. As we already said in the previous sections, the way in which we evaluate SSL methods is by evaluating how downstream tasks perform after the SSL phase. Of course the evaluation on the downstream task might depends by many factors: the chosen dataset, the network used for the encoding, the hyper-parameters used for the methods the type of augmentations applied and so on. In this section I tried to use the results taken from the papers of the considered methods, from survey [10] and from this paper [11]. In order to have a fair comparison I tried to collect results when the methods have been compared with the same encoder, and I also compared the methods on different datasets.
In table 1 we report the top-1 and top-5 accuracy of the considered methods when tested for classification on the ImageNet dataset and also the performances of a supervised model trained directly without SSL. All the methods uses as feature extractor a ResNet50 which is frozen after the SSL phase, and for the classification we only train a linear classifier which uses as inputs the representations of the frozen ResNet50 (sadly for some model we don't have the top-5 accuracy). In term of performances PIRL and CPC are the two worst models, while CMC does slightly better. SWAV and BYOL are by far the two best performing models, even if they do not reach the top-1 accuracy of the supervised model. MoCo and SimCLR are quite better than PIRL, CPC and CMP, but not as good as BYOL and SWAV.

Method	**Architecture**	**ImageNet**	
		Top1	Top5
Supervised	ResNet50	76.5	-
PIRL	ResNet50	63.6	-
CPCv2	ResNet50	63.8	85.3
CMC	ResNet50	66.2	87
SimCLR	ResNet50	69.3	89.0
MoCov2	ResNet50	71.1	-
BYOL	ResNet50	74.3	91.6
SwAV	ResNet50	75.3	-

Table 1: Accuracy of the SSL methods using linear probing for fine-tuning

Table 2 shows the performances of the methods in a semi-supervised learning scenario. Basically after having performed the SSL phase we fine-tune the models using in one case the 1% and in the other case the 10% of the dataset. We report also different versions of the same model but using a different encoders. If we only look at the models that use the ResNet50 the raking of the model is the same that we obtained in the case of the linear probing. Here we can also see that the network used for the encoding has of course a big impact on the performances, for instance CPCv2 with a ResNet161 encoder reaches an higher top-5 accuracy than SWAV and BYOL with a ResNet50.

Method	Architecture	ImageNet 1%		ImageNet 10%	
		Top1	Top5	Top1	Top5
Supervised	ResNet50	25.4	48.4	56.4	80.4
PIRL	ResNet50	30.7	57.2	60.4	83.8
SimCLR	ResNet50	48.3	75.5	65.6	87.8
BYOL	ResNet50	53.2	78.4	68.8	89.0
SwAV	ResNet50	53.9	78.5	70.2	89.9
CPCv2	ResNet161	-	77.9	-	91.2
SimCLR	ResNet50 (4×)	63.0	85.8	74.4	92.6
BYOL	ResNet50 (2×)	71.2	89.5	77.7	93.7

Table 2: Semi-supervised learning accuracy

For both tables 1 and 2 the results are taken from the original papers of the methods, so the training conditions might be different.
In tables 3 and 4 we report the accuracy for image classification task of the considered methods on multiple datasets using the same encoder for every method (a ResNet50). In table 3 the pre-trained feature extractor is kept frozen and the classification is performed using multinomial logistic regression, while in table 4 the whole architecture is fine-tuned with SGD, adding a MLP at the end of the encoder. In the right-most column we report the average accuracy across all the datasets.

	Imagenet	Aircraft	Calthech101	Cars	CIFAR10	CIFAR100	DTD	Flowers	Food	Pets	SUN387	VOC2007	Average
Supervised	77.20	43.59	90.18	44.92	91.42	73.90	72.23	89.93	69.49	91.45	60.49	83.60	73.75
PIRL	61.70	37.08	74.48	28.72	82.53	61.26	68.99	83.60	64.65	71.36	53.89	76.61	63.92
SimCLR	69.30	44.90	90.05	43.73	91.18	72.73	74.20	90.87	67.47	83.33	59.21	80.77	72.59
MoCo-v2	71.10	41.79	87.92	39.31	92.28	74.90	73.88	90.07	68.95	83.30	60.32	82.69	72.31
BYOL	74.30	53.87	91.46	56.40	93.26	77.86	76.91	94.50	73.01	89.10	59.99	81.14	77.05
SWAV	75.30	54.04	90.84	54.06	93.99	79.58	77.02	94.62	76.62	87.60	65.58	83.68	77.97

Table 3: Accuracy of linear probing on different datasets using ResNet50

	Aircraft	Calthech101	Cars	CIFAR10	CIFAR100	DTD	Flowers	Food	Pets	SUN387	VOC2007	Average
Supervised	83.50	91.01	82.61	96.39	82.91	73.30	95.50	84.60	92.42	63.56	84.76	84.60
PIRL	72.68	70.83	61.02	92.23	66.48	64.26	89.81	74.96	76.26	50.38	69.90	71.71
SimCLR	81.06	90.35	83.78	97.07	84.53	71.54	93.75	82.40	84.10	63.31	82.58	83.13
MoCo-v2	79.87	84.38	75.20	96.45	71.33	69.47	94.35	76.78	78.80	55.77	71.71	77.74
BYOL	79.45	89.40	84.60	97.01	83.95	73.62	94.48	85.54	89.62	63.96	82.70	84.03
SWAV	83.08	89.85	86.76	96.78	84.37	75.16	95.46	87.22	89.05	66.24	84.66	85.33

Table 4: Accuracy of fine-tuning on different datasets using ResNet50

Even in these experiments in general SWAV performs slightly better than BYOL (even if in not all the datasets). SimCLR and MoCo have similar performances while PIRL performs significantly worse. In this cases for some datasets the performances of the best self-supervised datasets are even slightly better than those of the directly trained supervised models.
Sadly for other tasks aside image classification I couldn't find a single dataset on which all the methods have been tested. Table 5 shows the results of PIRL, MoCO-v2 and SWAV for an object detection task on the VOC07+12 dataset using a Faster R-CNN. Again PIRL is the worst model, while for two of the three metrics MoCo-v2 is a bit better than SWAV. In table 6 we report the performances

of MoCo, SimCLR and BYOL in a semantic segmentation task on the VOC2012 dataset using again a Faster R-CNN. BYOL again is the best model and SimCLR does a bit better than MoCo.

	AP	AP_{50}	AP_{75}
Supervised	53.5	81.3	58.8
PIRL	54.0	80.7	59.7
MoCo-v2	57.4	82.5	64.0
SWAV	56.1	82.6	62.7

Table 5: Object detection VOC dataset

	AP_{50}	mIoU
Supervised	74.4	74.4
MoCo	74.9	72.5
SimCLR	75.2	75.2
BYOL	77.5	76.3

Table 6: Image segmentation VOC dataset

5 Strengths and weaknesses

The performances comparison shows that CPC, PIRL and CMC perform worse than the other methods, while the two best models are SWAV and BYOL. Moco-v2 and SimCLR are not as good as SWAV and BYOL but they are better than CPC, PIRL and CMC, and SimCLR performs a slightly better than MoCo-v2.
Among all the methods considered CPC was the first one to be proposed, and it is very different from all the other methods, since it uses the idea of creating a grid of embeddings and train the auto-regressive model to predict future representation of these embeddings. CPC framework has been heavily simplified in CMC, removing the auto-regressive part, and introducing the idea of contrasting different views of the image. Moreover in CMC the views are produced separating the image channels and not by applying transformation to the original image. PIRL seems similar to CMC but actually in CMC the networks used to encode the different views of the images are specific for each view, so they learn information specific to the views, while in PIRL contrastive learning is employed to learn a single embedding networks which produces representations invariant to the specific characteristic of the different views created with data augmentation. Both PIRL and CMC uses a memory bank to store samples to use in the contrastive loss. SimCLR is very similar to PIRL but instead of using the memory bank it uses a very large batch size during the training for the pretext task and it also apply the MLP projection to the image representation computed by the CNN. The main characteristic of MoCo is the usage of a queue of embeddings of the last K mini-batches, instead of a classic a memory bank. MoCo has been improved in MoCo-v2 taking from SimCLR the ideas of using heavier data augmentation and the usage of the MLP projection head.
Both SWAV and BYOL differ from all the other methods since they use predictive pretext tasks instead of contrastive learning. BYOL uses the idea of applying a classifier to the output of the online network to predict the output of the target network. In SWAV instead there is no distinction between target and online network, and the main characteristic is the usage of clustering to perform the swapped prediction problem. BYOL is more straightforward than SWAV, since in BYOL we simply compute the embeddings of the two inputs and we use the classifier to predict the embedding of the target network from the embedding of the online network, using the mean squared error as loss function, while in SWAV we also need to solve the optimization problem to compute the clusters assignment of the inputs.
One of the main difference among the methods is the technique they use to retrieve the negative samples to use in the loss. CPC didn't consider this problem at all, PIRL and CMC use a large

memory bank, MoCo uses the queue of the embedding of the last K mini-batches which is less space and time demanding than the memory bank, while SimCLR, SWAV and BYOL just use large batch sizes. Using large batch sizes instead of an explicit memory bank has of course the advantage that we spare time and computations for handling the memory, but we are limited by the memory size of the GPU. Since SWAV and BYOL doesn't use the idea of contrasting positive and negative pairs, they have the advantage that they don't need to use those techniques, and moreover they even reach better performances than the other methods.

6 Conclusion

In conclusion, this work explored various self-supervised learning methods for computer vision. The general framework of self-supervised learning was discussed, highlighting the advantages of learning from unlabeled data and the potential of transferring learned representations to downstream tasks. Different self-supervised learning methods were described in detail and compared. The empirical results showed that the two best performing models on the downstream tasks are BYOL and SWAV, while CPC, CMC and PIRL are the worst performer. SimCLR and MoCo are not as good as BYOL and SWAV but still better than the worst three.

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