Aalto University

CS-E4890: Deep Learning
Learning with few labeled examples

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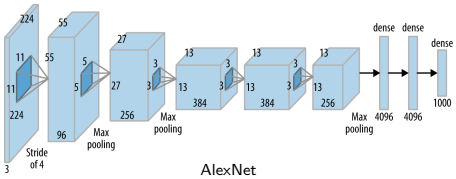
Motivation

- Deep learning is data hungry. To learn to classify handwritten digits, we need thousands of samples, to learn to classify natural images we need millions of images.
- Suppose we have a custom classification task, for example, we need to classify images to custom classes (not covered by imageNet). What can we do?
  - Collect a lot of training examples and label them.
    - Time consuming and expensive.
    - Sometimes collecting new examples is impossible.
  - Transfer learning
  - Semi-supervised learning
  - Self-supervised learning
  - Few-shot learning (meta learning)

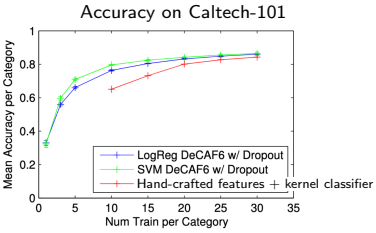
Transfer learning

Transfer learning: Image classification

- Features that are useful for some tasks can be useful for other tasks in the same domain.
- For image classification tasks, it is common to fine-tune the last layer of a deep neural network pre-trained on imageNet (there is a bunch of them in PyTorch).
- Example: Donahue et al. (2013) use outputs from the sixth layer of AlexNet and as features for a classifier trained on Caltech-101 dataset.



AlexNet

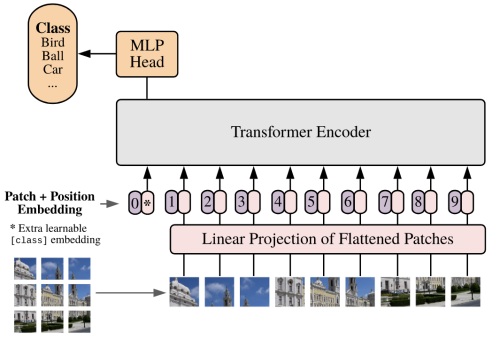


- A common way of doing transfer learning on vision tasks: use a ResNet pre-trained on ImageNet as a feature extractor, train the last linear layer on a target dataset.

Transfer learning with Vision Transformers (Dosovitskiy et al., 2020)

- We have seen transfer learning with BERT on natural language understanding tasks.

- Transformers has been shown to work well in the vision domain as well.
- Vision Transformer (ViT)
  - split an image into fixed-size patches
  - linearly embed each of them
  - add position embeddings
  - feed the resulting sequence of vectors to a standard Transformer encoder.
  - In order to perform classification, add an extra learnable "classification token" to the sequence.

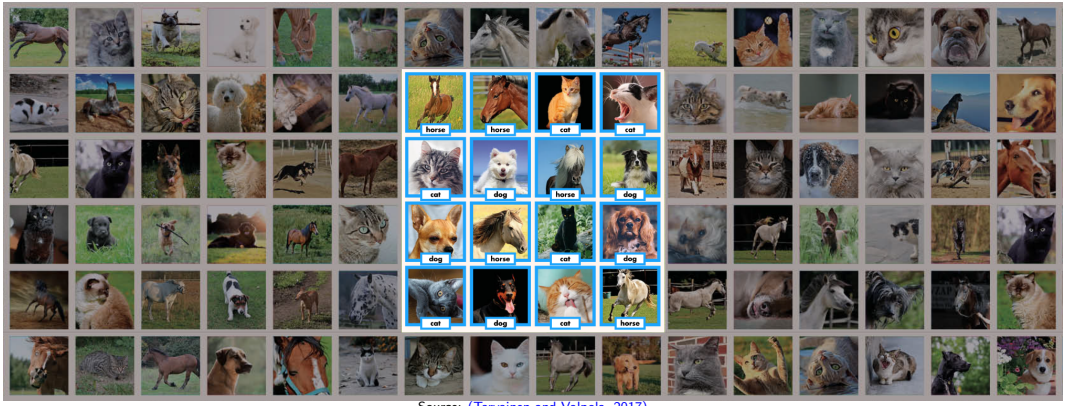


- ViT is pre-trained on large datasets and then fine-tuned to (smaller) downstream tasks.

Semi-supervised learning

Semi-supervised classification

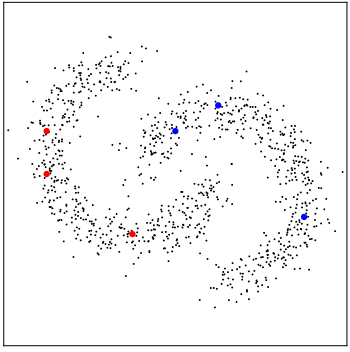
- Semi-supervised classification: few labeled examples, many unlabeled examples.



Source: (Tarvainen and Valpola, 2017)

When semi-supervised learning is possible?

- Semi-supervised learning is possible when the knowledge on $p(\mathbf{x})$ that one gains through the unlabeled data carries information that is useful in the inference of $p(\mathbf{y} \mid \mathbf{x})$.
- In the hypothetical example on the right, modeling the distribution of unlabeled data can improve the classification accuracy.
  - The labels can be propagated to the unlabeled data in the same cluster yielding better classification accuracy.



Red and blue dots: labeled samples

Black dots: unlabeled samples

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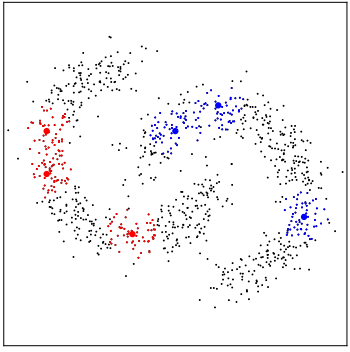

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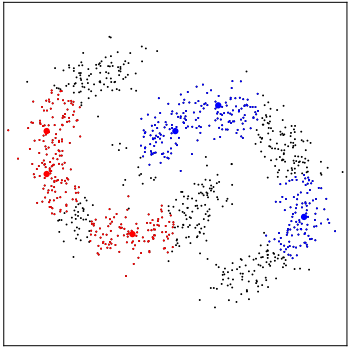

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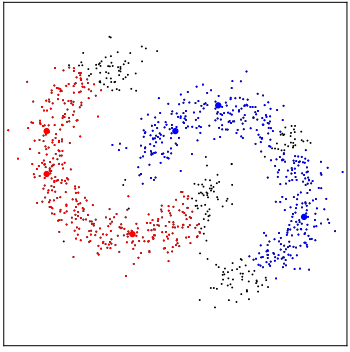

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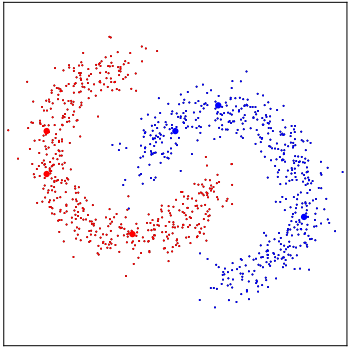

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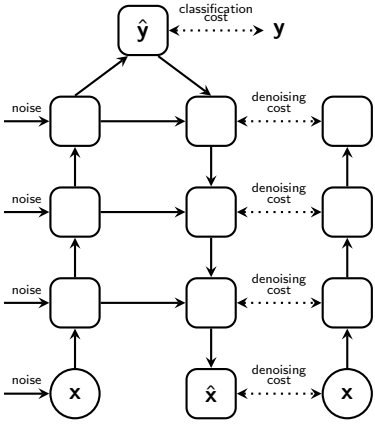
Ladder networks (Rasmus et al., 2015)

- Rasmus et al. (2015) showed that a denoising autoencoder trained on two tasks (denoising and classification) can be very efficient in semi-supervised learning.
- The architecture resembles a ladder (or a U-net).
- Denoising task: produce a clean input at the bottom (use both labeled and unlabeled examples to compute the loss).
- Classification task: produce the correct label at the bottleneck (use labeled examples to compute the loss).

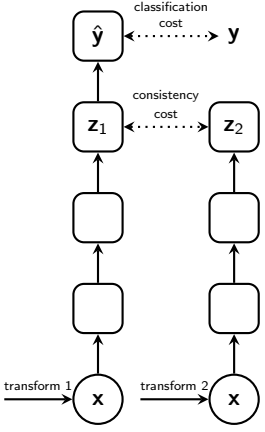


Π-model (Laine and Aila, 2016): Consistency-based semi-supervised learning

- Laine and Aila (2016) proposed a simplification of the Ladder networks that does not contain the top-down pass.
- There are two copies of the same network performing computations for $\mathbf{x}_1$ and $\mathbf{x}_2$, which is the same training example changed with different transformations.
- The cost for unlabeled data is

$$\text{consistency cost} = \|\mathbf{z}_1 - \mathbf{z}_2\|^2 = \|f(\mathbf{x}_1) - f(\mathbf{x}_2)\|^2$$

  - The gradients propagate through both networks, $\mathbf{z}$ is the input of the softmax (logit).
  - The model resembles siamese networks (Bromley et al., 1993).
- The intuition: we do not know the correct output for unlabeled data but we know that the output should not change for a transformed input.



Mean Teacher (Tarvainen and Valpola, 2017)

- Since the Π-model, the majority of semi-supervised methods maximize the consistency between different transformations of the same training examples.

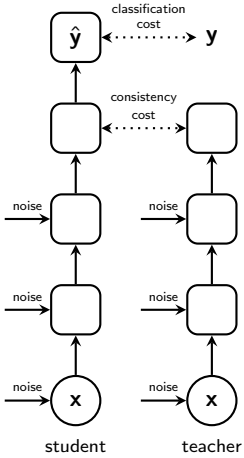
- Mean teacher: Instead of using two identical networks, one network (teacher) is obtained by computing exponential moving average (EMA) of the weights of the other (student) network:

$$\boldsymbol{\theta}'_t = \gamma \boldsymbol{\theta}'_{t-1} + (1-\gamma)\boldsymbol{\theta}_t$$

  - Using a fixed target usually stabilizes training (gradients are propagated only through the student).
  - EMA removes the noise caused by stochastic gradient descent, which makes the teacher more accurate than the student.

- The same consistency cost is used:

$$\text{consistency cost} = \left\| f(\mathbf{x}_1, \boldsymbol{\theta}_t) - f(\mathbf{x}_2, \boldsymbol{\theta}'_t) \right\|^2$$



Evolution of consistency-based semi-supervised methods

Algorithm	Student augment.	Teacher augment.	Teacher label post-processing	CIFAR-10 accuracy 4K labels (from here)
Fully supervised Wide ResNet with 50K labels	–	–	–	94.6
Π-Model (Laine and Aila, 2016)	Weak	Weak	–	87.84
VAT (Miyato et al., 2017)	Adversarial	–	–	88.64
Mean Teacher (Tarvainen and Valpola, 2017)	Weak	Weak	–	93.72
UDA (Xie et al., 2019)	Strong	Weak	Sharpening	94.73
MixMatch (Berthelot et al., 2019)	Weak	Weak	Sharpening	93.76
ReMixMatch (Berthelot et al., 2019)	Strong	Weak	Sharpening	94.86
FixMatch (Sohn et al., 2020)	Strong	Weak	Pseudo-labeling	95.69

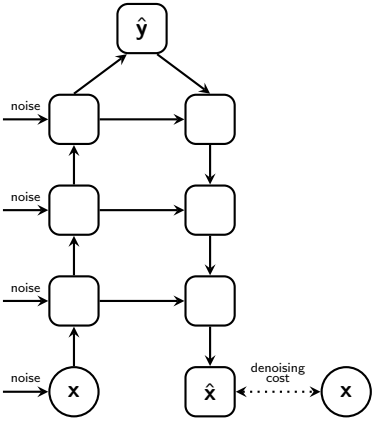
- Weak augmentations: translation, flip, Gaussian noise. Strong augmentations: uniformly sample all image processing transformations from the Python Image Library (PIL).
- Label sharpening, pseudo-labeling: reduce the entropy of the targets.

Self-supervised learning

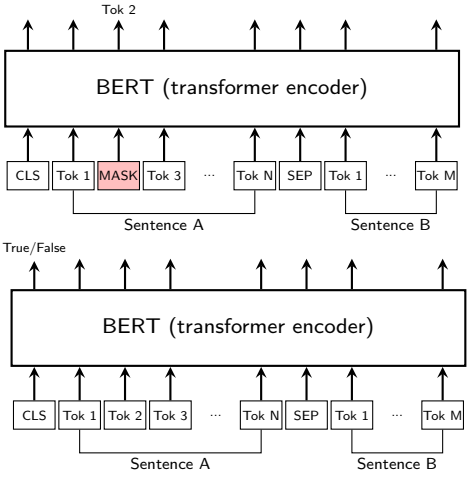
Self-supervised learning

- The assumption that is made in semi-supervised learning: The unlabeled examples belong to the same classes. This can be difficult to assure in many practical applications.
- Can we lean useful representations in a completely unsupervised manner?
- Self-supervised learning: Invent an auxiliary task that can be learned in an unsupervised manner and use the developed features for the downstream task.
- In order to succeed, the auxiliary task should be relevant for the downstream task.

Examples of self-supervised learning models



Ladder networks

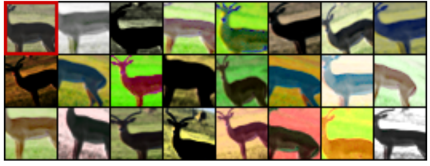


Discriminative unsupervised feature learning (Dosovitskiy et al., 2014)

- One of the early works on self-supervised training.
- A convolutional neural network is pre-trained using an artificially created learning task.
  - N patches of size 32×32 are sampled from different images at varying positions and scale.
  - Each patch is transformed multiple times using (a composition of elementary) transformations.
  - The task is to classify a transformed image patch to one of the N classes that correspond to the original N patches.
- The features produced by the CNN are used as inputs of a support vector machine classifier.

sampled patches

transformed patches



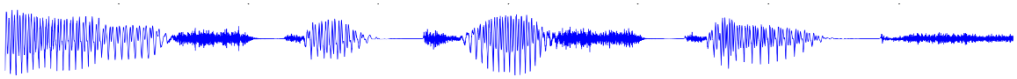
elementary transformations used: translation, scaling, rotation, contrast (raise S and V components of the HSV color representation), color (change the H component of the HSV representation)

Contrastive Predictive Coding

(van den Oord et al., 2018)

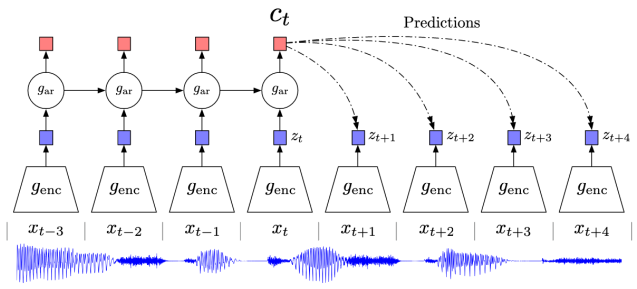
Motivation

- The goal is to learn representations that encode the underlying shared information between different parts of the (high-dimensional) signal. At the same time we want to discard low-level information and noise that is more local.
- When predicting further in the future, the amount of shared information becomes much lower, and the model needs to infer more global structure. These 'slow features' that span many time steps are often more interesting (e.g., phonemes and intonation in speech, objects in images, or the story line in books.)



Contrastive Predictive Coding (CPC): The model

- A non-linear encoder g_{enc} maps the input sequence of observations x_t to a sequence of latent representations $z_t = g_{\text{enc}}(x_t)$, potentially with a lower temporal resolution.
- Next, an autoregressive model g_{ar} summarizes all $z \leq t$ in the latent space and produces a context latent representation $c_t = g_{\text{ar}}(z \leq t)$.

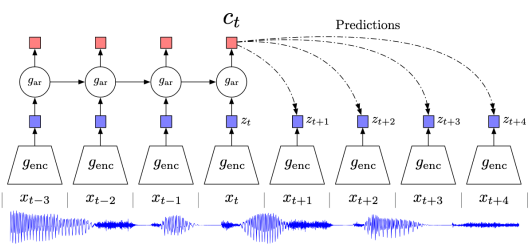


CPC: Contrastive loss

- The task: Given the context c_t, select the correct future code $z_{t+k} = g_{\text{enc}}(x_{t+k})$ after k steps among N alternatives $\{z_{t+k}, z_{\tau_1}, ..., z_{\tau_{N-1}}\}$.
- The alternatives $z_\tau = g_{\text{enc}}(x_\tau)$ are selected as encoder outputs produced for inputs x_τ randomly selected from the dataset (for example, from the same input sequence).
- The loss is the categorical cross-entropy of selecting the correct encoding:

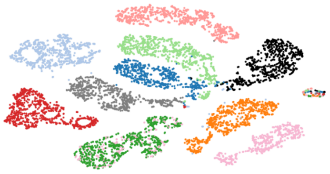
$$\mathcal{L} = -\log \frac{\exp(z_{t+k}^\top W_k c_t)}{\sum_j \exp(z_{\tau_j}^\top W_k c_t)}$$

- The logits produced by the classifier are postulated to have the form $z_\tau^\top W_k c_t$.



CPC: Results for audio data

- The quality of developed representations are tested by training a classifier using representations c_t as features on the phone classification task:
  - linear classifier: 64.6
  - MLP classifier: 72.5
- CPC captures both speaker identity and speech contents.



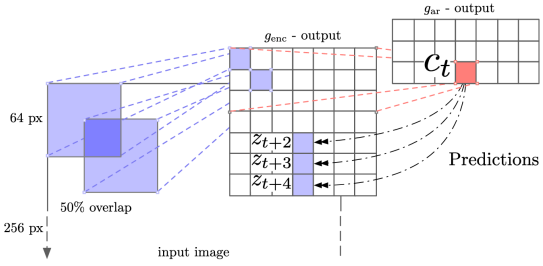
t-SNE visualization of audio (speech) representations for a subset of 10 speakers (out of 251). Every color represents a different speaker.

Method	ACC
Phone classification	
Random initialization	27.6
MFCC features	39.7
CPC	64.6
Supervised	74.6
Speaker classification	
Random initialization	1.87
MFCC features	17.6
CPC	97.4
Supervised	98.5

Classification accuracy on audio data. Phone classification: 41 classes Speaker classification: 251 classes. random initialization: random g_{enc} and g_{ar}

CPC for image data

- Contrastive Predictive Coding for images:



- The quality of developed representations are tested by training a linear classifier using RNN outputs c_t as input features.

Method	Top-5 ACC
Motion Segmentation (MS)	48.3
Exemplar (Ex)	53.1
Relative Position (RP)	59.2
Colorization (Col)	62.5
Combination of MS + Ex + RP + Col	69.3
CPC	**73.6**

ImageNet top-5 unsupervised classification results.

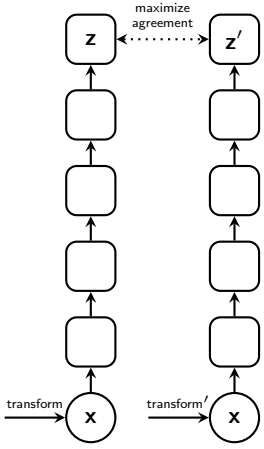
A Simple Framework for Contrastive Learning (SimCLR)

(Chen et al., 2020a, 2020b)

SimCLR (Chen et al., 2020a)

- SimCLR can be seen as the siamese networks processing two different augmentations of the same image (as in the Π-model, Mean Teacher) combined with the CPC contrastive loss.
  - Sample a minibatch of N examples.
  - Augment each example with two different transformations, which results in $2N$ data points.
  - Process each example with a deep neural network $\mathbf{z} = g(f(\mathbf{x}))$.
  - The training task is similar to CPC: For each image in the minibatch, we need to select the other image that was produced with the other transformation of the same original image among $2N - 1$ alternatives

$$l_{i,j} = -\log \frac{\exp(\text{sim}(\mathbf{z}_i, \mathbf{z}_j/\tau))}{\sum_{k=1}^{2N} \mathbb{1}_{[k \neq i]} \exp(\text{sim}(\mathbf{z}_i, \mathbf{z}_k)/\tau)}$$



SimCLR (Chen et al., 2020a)

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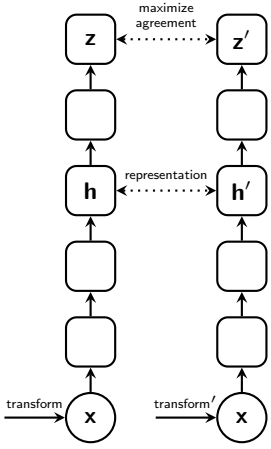
- The cosine similarity is used:

$$\text{sim}(\mathbf{u}, \mathbf{v}) = \mathbf{u}^\top \mathbf{v} / \|\mathbf{u}\| \, \|\mathbf{v}\|$$

- As representation $\mathbf{h}$, we take the output of an intermediate layer (two layers before the output).
  - The intuition: The formulated task of contrastive learning needs development of the right features but the downstream task is likely to be different and to require a different post-processing head.



SimCLR augmentations

- Three augmentations are sequentially applied:

original

1) random cropping followed by resize to the original size

2) random color distortions

3) random Gaussian blur

- Random cropping and color distortions give the largest boost in performance.
- It is important to apply both transformations for good performance. Why?

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- Random cropping and color distortions give the largest boost in performance.
- It is important to apply both transformations for good performance. Why?
  Because with one transformation only it is relatively easy to find matching pairs of images.

Linear classifier trained on top of SimCLR representations

Method	Architecture	Param (M)	Top 1	Top 5
Methods using ResNet-50:				
Local Agg.	ResNet-50	24	60.2	-
MoCo	ResNet-50	24	60.6	-
PIRL	ResNet-50	24	63.6	-
CPC v2	ResNet-50	24	63.8	85.3
SimCLR (ours)	ResNet-50	24	**69.3**	**89.0**
Methods using other architectures:				
Rotation	RevNet-50 (4×)	86	55.4	-
BigBiGAN	RevNet-50 (4×)	86	61.3	81.9
AMDIM	Custom-ResNet	626	68.1	-
CMC	ResNet-50 (2×)	188	68.4	88.2
MoCo	ResNet-50 (4×)	375	68.6	-
CPC v2	ResNet-161 (∗)	305	71.5	90.1
SimCLR (ours)	ResNet-50 (2×)	94	74.2	92.0
SimCLR (ours)	ResNet-50 (4×)	375	**76.5**	**93.2**

ImageNet accuracies of linear classifiers trained
on representations learned with different self-supervised methods

Semi-supervised training with SimCLR

- The whole base network is fine-tuned on the few labeled data without regularization.

Method	Architecture	Label fraction (Top 5) 1%	10%
Supervised baseline	ResNet-50	48.4	80.4
Methods using other label-propagation:			
Pseudo-label	ResNet-50	51.6	82.4
VAT+Entropy Min.	ResNet-50	47.0	83.4
UDA (w. RandAug)	ResNet-50	-	88.5
FixMatch (w. RandAug)	ResNet-50	-	89.1
S4L (Rot+VAT+En. M.)	ResNet-50 (4×)	-	91.2
Methods using representation learning only:			
InstDisc	ResNet-50	39.2	77.4
BigBiGAN	RevNet-50 (4×)	55.2	78.8
PIRL	ResNet-50	57.2	83.8
CPC v2	ResNet-161(∗)	77.9	91.2
SimCLR (ours)	ResNet-50	75.5	87.8
SimCLR (ours)	ResNet-50 (2×)	83.0	91.2
SimCLR (ours)	ResNet-50 (4×)	**85.8**	**92.6**

ImageNet accuracy of models trained with few labels

Bootstrap your own latent (BYOL)

(Grill et al., 2020)

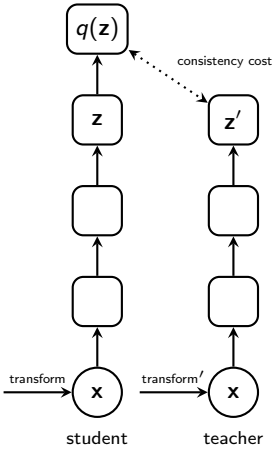
Bootstrap your own latent (BYOL) (Grill et al., 2020)

- BYOL can be seen as an extension of the Mean Teacher to the fully unsupervised scenario:
  - The teacher network is obtained by computing exponential moving average of the weights of the student.
  - The two networks process two different transformations of the same example.
  - The objective is

$$\text{consistency cost} = \left\| q(\mathbf{z}) - \mathbf{z}' \right\|^2$$

    where $\mathbf{z} = f(\mathbf{x}, \boldsymbol{\theta}_t)$, $\mathbf{z}' = f(\mathbf{x}', \boldsymbol{\theta}'_t)$

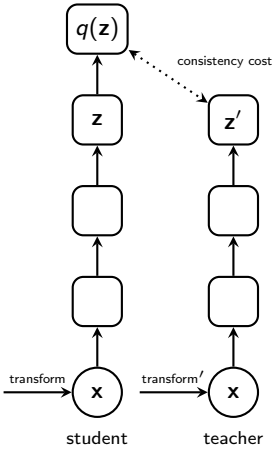
- Differences:
  - Use strong augmentations (same set of augmentations as in SimCLR).
  - Use an extra predictor MLP $q(\mathbf{z})$ in the student network.



Bootstrap your own latent (BYOL) (Grill et al., 2020)

$$\text{consistency cost} = \left\| q(\mathbf{z}) - \mathbf{z}' \right\|^2$$

- The representations can collapse: the network can learn to produce the same output $\mathbf{z}$ for any input $\mathbf{x}$, which would yield a zero consistency cost.
- In practice, this does not happen for the given architecture. In fact, the representations collapse if the predictor network $q(\mathbf{z})$ is removed.



BYOL: Linear evaluation

Method	Top-1	Top-5
Local Agg.	60.2	-
PIRL [35]	63.6	-
CPC v2 [32]	63.8	85.3
CMC [11]	66.2	87.0
SimCLR [8]	69.3	89.0
MoCo v2 [37]	71.1	-
InfoMin Aug. [12]	73.0	91.1
BYOL (ours)	**74.3**	**91.6**

(a) ResNet-50 encoder.

Method	Architecture	Param.	Top-1	Top-5
SimCLR [8]	ResNet-50 (2×)	94M	74.2	92.0
CMC [11]	ResNet-50 (2×)	94M	70.6	89.7
BYOL (ours)	ResNet-50 (2×)	94M	77.4	93.6
CPC v2 [32]	ResNet-161	305M	71.5	90.1
MoCo [9]	ResNet-50 (4×)	375M	68.6	-
SimCLR [8]	ResNet-50 (4×)	375M	76.5	93.2
BYOL (ours)	ResNet-50 (4×)	375M	78.6	94.2
BYOL (ours)	ResNet-200 (2×)	250M	**79.6**	**94.8**

(b) Other ResNet encoder architectures.

ImageNet accuracies of linear classifiers trained
on representations learned with different self-supervised methods

BYOL: Semi-supervised training

- The whole base network is fine-tuned on the few labeled data with spatial augmentations, i.e., random crops with resize and random flips.

Method	Top-1		Top-5	
	1%	10%	1%	10%
Supervised [77]	25.4	56.4	48.4	80.4
InstDisc	-	-	39.2	77.4
PIRL [35]	-	-	57.2	83.8
SimCLR [8]	48.3	65.6	75.5	87.8
BYOL (ours)	**53.2**	**68.8**	**78.4**	**89.0**

(a) ResNet-50 encoder.

Method	Architecture	Param.	Top-1		Top-5	
			1%	10%	1%	10%
CPC v2 [32]	ResNet-161	305M	-	-	77.9	91.2
SimCLR [8]	ResNet-50 (2×)	94M	58.5	71.7	83.0	91.2
BYOL (ours)	ResNet-50 (2×)	94M	62.2	73.5	84.1	91.7
SimCLR [8]	ResNet-50 (4×)	375M	63.0	74.4	85.8	92.6
BYOL (ours)	ResNet-50 (4×)	375M	69.1	75.7	87.9	92.5
BYOL (ours)	ResNet-200 (2×)	250M	**71.2**	**77.7**	**89.5**	**93.7**

(b) Other ResNet encoder architectures.

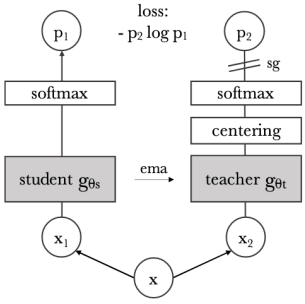
ImageNet accuracy of models trained with few labels

Self-Supervised Vision Transformers (DINO)

(Caron et al., 2021)

Self-Supervised Vision Transformers (DINO) (Caron et al., 2021)

- Self-supervised learning with Vision Transformers.
- The model passes two different random transformations of an input image to the student and teacher networks.
- The output of the teacher network is centered with a mean computed over the batch. Each networks outputs a K-dimensional feature that is normalized with a temperature softmax over the feature dimension. Their similarity is then measured with a cross-entropy loss.
- The teacher parameters are updated with an exponential moving average (ema) of the student parameters.



Unsupervised object segmentations with DINO

- Self-attention of the [CLS] token on the heads of the last layer. This token is not attached to any label nor supervision.

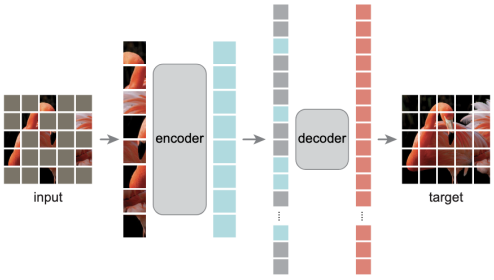
- These maps show that the model automatically learns class-specific features leading to unsupervised object segmentations.

Masked Autoencoders (MAE)

(He et al., 2021)

Masked Autoencoders (He et al., 2021)

- Training task: mask random patches of the input image and reconstruct the missing pixels.
- The encoder that operates only on the visible subset of patches (without mask tokens).
- A lightweight decoder reconstructs the original image from the latent representation and mask tokens.



- The approach allows for learning high-capacity models that generalize well: a vanilla ViT-Huge model achieves the best accuracy (87.8%) among methods that use only ImageNet-1K data.
- Transfer performance in downstream tasks outperforms supervised pre-training and shows promising scaling behavior.

Few-shot learning

Few-shot learning

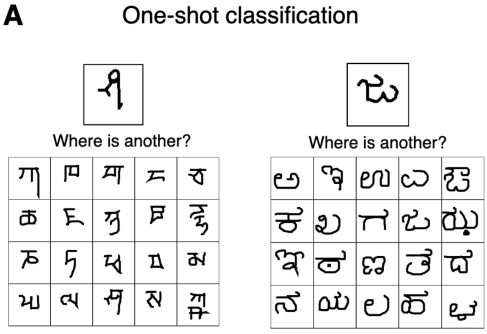
- Humans can learn new concepts from just a single example:

drone

segway

- Yet machine learning algorithms typically require thousands of examples to perform with similar accuracy (Lake et al., 2015).
- Few-shot learning: How can we train an accurate model using a very small amount of training data?

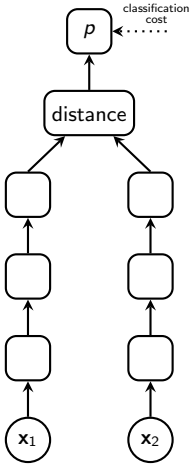
- The problem of few-shot learning attracted a lot of attention after releasing the Omniglot challenge (Lake et al., 2015).



Part A of Omniglot challenge: Two trials of one-shot classification, where a single image of a new character is presented (top) and the goal is to select another example of that character amongst other characters from the same alphabet (in the grid below).

Siamese networks for one-shot learning (Koch et al., 2015)

- Consider the task of *one-shot* classification: building a classifier from one training example.
- A siamese neural network (Bromley et al., 1993) is trained to compare a pair of examples to decide whether they belong to the same class or not (binary classification):
  - Twin networks which accept distinct inputs
  - The output is computed using a distance (e.g., Euclidean) between the highest-level feature representations of the twin networks.
  - The network is trained on pairs of positive (same class) and negative (distinct classes) examples.
- Works for one-shot learning, few-shot requires tweaking.

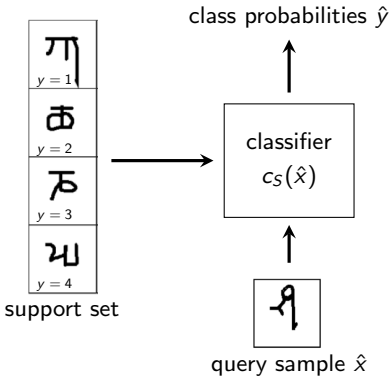


Matching networks (Vinyals et al., 2016)

- We wish to map from a (small) support set of k examples of image-label pairs $S = \{(x_i, y_i)\}_{i=1}^{k}$ to a classifier $c_S(\hat{x})$.

$$S \rightarrow c_S(\hat{x})$$

- The classifier $c_S(\hat{x})$ defines a probability distribution $\hat{y}$ over classes in the support set for a query example $\hat{x}$.
- Matching networks: Parameterize this mapping $S \rightarrow c_S(\hat{x})$ as a neural network.



Matching networks: The model

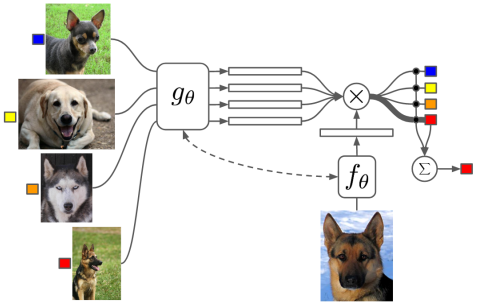
- The output of the classifier $c_S(\hat{x})$:

$$\hat{y} = \sum_{i=1}^{k} a(\hat{x}, x_i) y_i$$

with an attention mechanism a:

$$a(\hat{x}, x_i) = \frac{\exp(c(f(\hat{x}), g(x_i)))}{\sum_{j=1}^{k} \exp(c(f(\hat{x}), g(x_j)))}$$

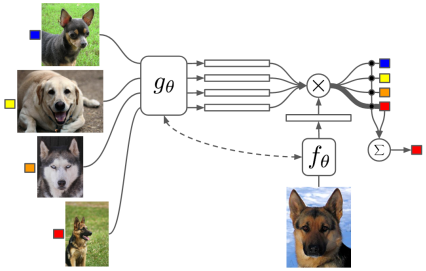
- f and g are parameterized as neural networks.



- Intuition: support samples whose representations $g(x_i)$ are close to the representation $f(\hat{x})$ of the query sample contribute more to the output.
- We tune the representations to work well in the few-shot learning scenario.

Matching networks: Episodic training

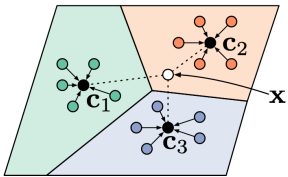
- N-way K-shot classification task: Each training example is a classification task with N classes and K training examples per class.
- One iteration of episodic training:
  - Select N classes by randomly sampling from the training set.
  - Select a support set by taking K random samples for each of the selected classes.
  - Select a query set (a few samples from the same classes as in the support set).
  - Do forward computations and compute the classification loss using the query samples.
  - Do backpropagation and update the parameters of the network.



Prototypical networks (Snell et al., 2017)

- Prototypical networks compute an M-dimensional representation $\mathbf{c}_k$, or prototype, of each class through an embedding function f_{θ}. Each prototype is the mean vector of the embedded support points belonging to its class:

$$\mathbf{c}_k = \frac{1}{|S_k|} \sum_{(x_i, y_i) \in S_k} f_{\theta}(x_i)$$



- Then they produce a distribution over classes for a query point x based on a softmax over distances to the prototypes in the embedding space:

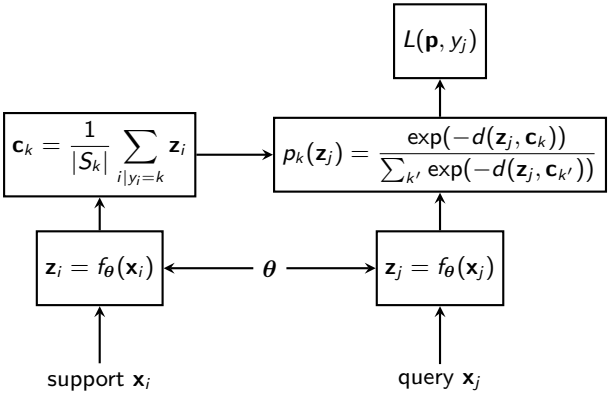
$$p(y = k \mid x) = \frac{\exp(-d(f_{\theta}(x), \mathbf{c}_k))}{\sum_{k'} \exp(-d(f_{\theta}(x), \mathbf{c}_{k'}))}$$

- In one-shot learning scenario, prototypical networks are equivalent to matching networks.

Prototypical networks: Training

One iteration of episodic training:

- The support set is used to compute the prototypes.
- The query set is used to compute the loss.
- Compute the gradients of the loss and update the parameters $\boldsymbol{\theta}$ of the embedding network.



Computational graph

Model-Agnostic Meta-Learning (MAML; Finn et al., 2017)

- We want to train a classifier $y = f_{\boldsymbol{\theta}}(\mathbf{x})$ to solve a new few-shot learning task.
- Learning can be done by performing a few iterations of gradient descent (GD).
- In the case of one iteration of GD:

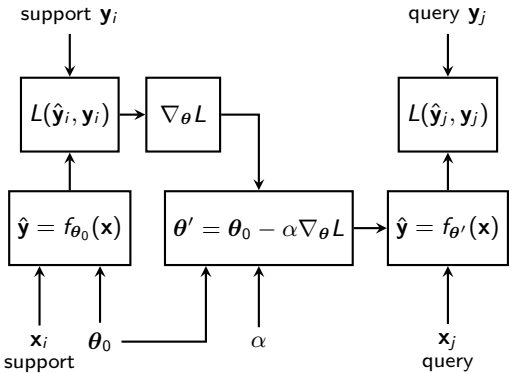
$$\boldsymbol{\theta}' \leftarrow \boldsymbol{\theta}_0 - \alpha \nabla_{\boldsymbol{\theta}} L((\mathbf{x}_1, \mathbf{y}_1), ..., (\mathbf{x}_k, \mathbf{y}_k))$$

  - $\{(\mathbf{x}_i, \mathbf{y}_i)\}_{i=1}^{k}$ are the few training examples (support set)
  - L is the loss function (for example, cross-entropy for classification tasks)
  - α is the learning rate
  - $\boldsymbol{\theta}_0$ is the vector of the initial values of the parameters
- The idea of meta-learning: we can learn initialization $\boldsymbol{\theta}_0$ and the learning rate α to minimize the loss (on the query set) after the GD-adaptation.

Model-Agnostic Meta-Learning: Training

One iteration of episodic training:

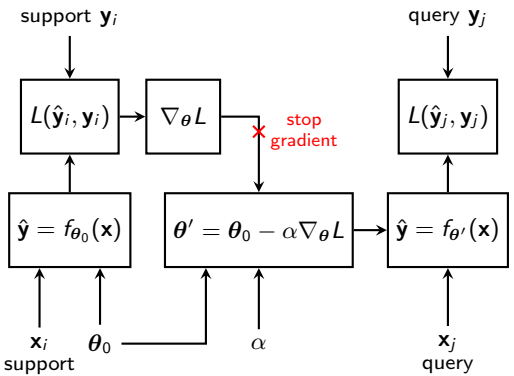
- Use the support set to compute the loss and its gradient $\nabla_{\boldsymbol{\theta}} L$.
- Compute adapted values $\boldsymbol{\theta}'$ of the parameters (as part of computational graph) with one (or a few) iteration of gradient descent.
- Use the query set to compute the loss with the adapted parameters $\boldsymbol{\theta}'$.
- Perform backpropagation and update parameters $\boldsymbol{\theta}_0$ and learning rate α.



Computational graph

Model-Agnostic Meta-Learning: First-order approximation

- MAML requires computation of gradient through gradient, which can be computationally expensive.
- The first-order approximation (which stops gradient propagation through $\nabla_{\boldsymbol{\theta}} L$) works almost equally well.

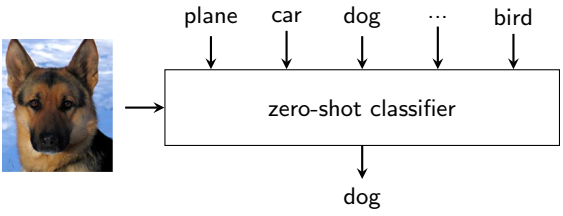


Computational graph

Zero-shot visual models with natural language supervision (CLIP, Radford et al., 2021)

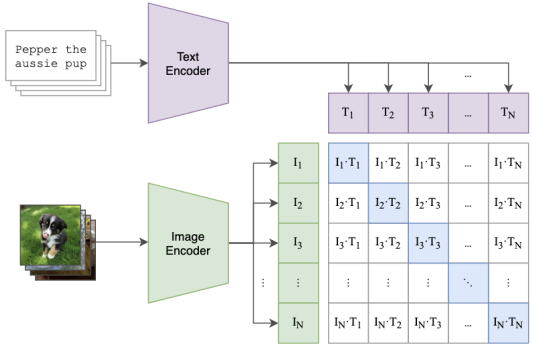
CLIP (Radford et al., 2021)

- Previous pre-training tasks for representation learning for images:
  - match different representations of the same image (e.g., SimCLR, BYOL)
  - use labels from classification tasks from the same domain (ResNet pre-trained on ImageNet, ViT pre-trained on huge labeled datasets)
- CLIP: learn image representations with supervision by natural language (textual descriptions of images).
- One of the goals: good zero-shot capabilities, that is learning to solve new classification tasks without training examples.



CLIP's contrastive learning task

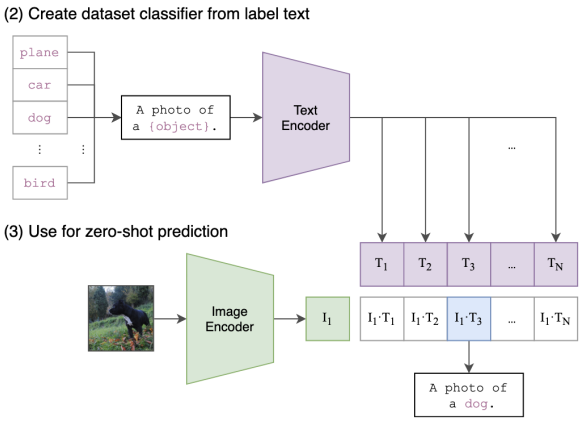
- Jointly train an image encoder and text encoder to maximize the cosine similarity of the image and text embeddings of the N real pairs in the batch while minimizing the cosine similarity of the embeddings of the $N^2 - N$ incorrect pairings.




```
# image_encoder - ResNet or Vision Transformer
# text_encoder  - CBOW or Text Transformer
# I[n, h, w, c] - minibatch of aligned images
# T[n, l]       - minibatch of aligned texts
# W_i[d_i, d_e] - learned proj of image to embed
# W_t[d_t, d_e] - learned proj of text to embed
# t             - learned temperature parameter

# extract feature representations of each modality
I_f = image_encoder(I) #[n, d_i]
T_f = text_encoder(T)  #[n, d_t]

# joint multimodal embedding [n, d_e]
I_e = l2_normalize(np.dot(I_f, W_i), axis=1)
T_e = l2_normalize(np.dot(T_f, W_t), axis=1)

# scaled pairwise cosine similarities [n, n]
logits = np.dot(I_e, T_e.T) * np.exp(t)

# symmetric loss function
labels = np.arange(n)
loss_i = cross_entropy_loss(logits, labels, axis=0)
loss_t = cross_entropy_loss(logits, labels, axis=1)
loss   = (loss_i + loss_t)/2
```

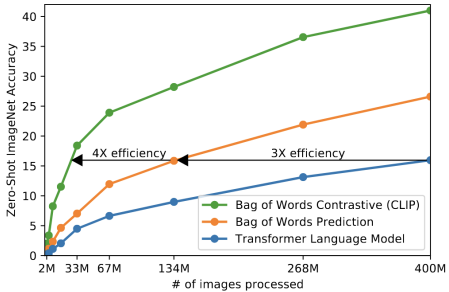
CLIP: Structure of the zero-shot classifier at test time

- Prompt engineering: create a short text using the name of the label. For example, 'plane' is converted to 'A photo of a plane'.
- Prompt engineering helps improve the zero-shot results.
- CLIP achieves impressive zero-shot accuracies in many image classification tasks. For example, 76.2% on ImageNet (without seeing ImageNet data), which is on par with a ResNet trained on ImageNet with labels.



The pre-training task of CLIP

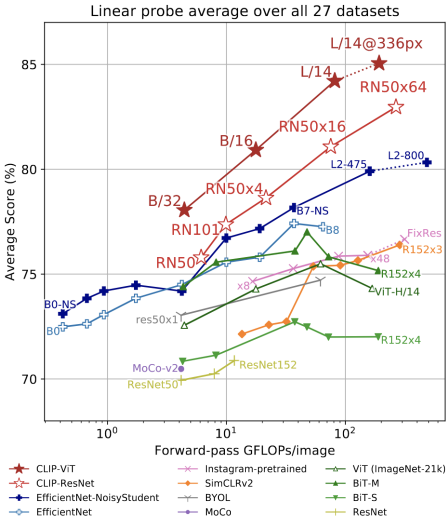
- The authors have tried three pre-training tasks:
  - Image CNN and text transformer from scratch to predict the caption of an image.
  - A model that predicts a bag-of-words encoding of the caption.
  - Contrastive learning: Given a batch of N (image, text) pairs, predict which of the $N \times N$ possible (image, text) pairings across a batch actually occurred.



- The contrastive learning approach learns much faster compared to the other two methods.
- This is natural because the test task (zero-shot classification of ImageNet) is similar to the training task: each caption can be seen as a separate class.

Linear probing of CLIP image features

- CLIP is trained on 400 million (image, text) pairs collected from the internet.
- The text encoder is a Transformer with the modifications from GPT-2.
- Image encoders: ResNets or Vision Transformers (ViT).
- Training times: 18 days on 592 V100 GPUs (largest ResNet), 12 days on 256 V100 GPUs (largest ViT).
- Natural language supervision provides a stronger signal for representation learning compared to classification tasks (compare CLIP-ViT vs ViT).
- ViT works better than ResNet in this task.

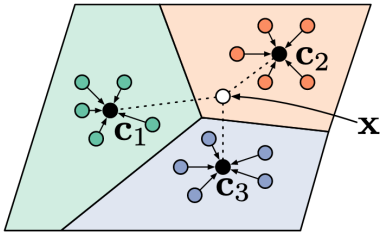


Home assignment

- You need to implement prototypical networks (Snell et al., 2017).

$$\mathbf{c}_k = \frac{1}{|S_k|} \sum_{(x_i, y_i) \in S_k} f_{\theta}(x_i)$$

$$p(y = k \mid x) = \frac{\exp(-d(f_{\theta}(x), \mathbf{c}_k))}{\sum_{k'} \exp(-d(f_{\theta}(x), \mathbf{c}_{k'}))}$$



Recommended reading

- Papers cited in the lecture slides.