Simple Summary of 23Summer Study

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1. Deep Metric Learning
2. Two Mainstreams
3. Learning Without Negative Pairs
4. Masked Image Model

1 Deep Metric Learning

2 Two Mainstreams

3 Learning Without Negative Pairs

4 Masked Image Model

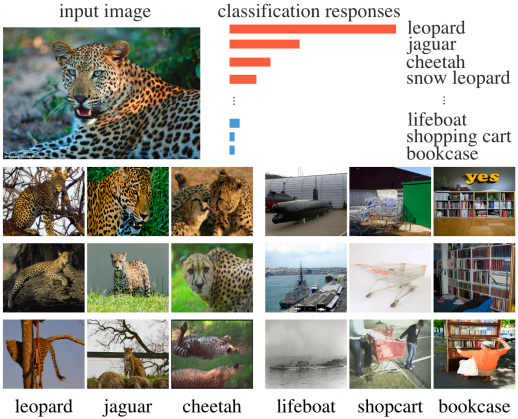
Deep Metric Learning

Learning a distance function over objects.

Given some input pairs $(\boldsymbol{x}_i, \boldsymbol{x}_j)$ and their similarities, y_{ij}. Task is to learn a function d which conform the similarities.

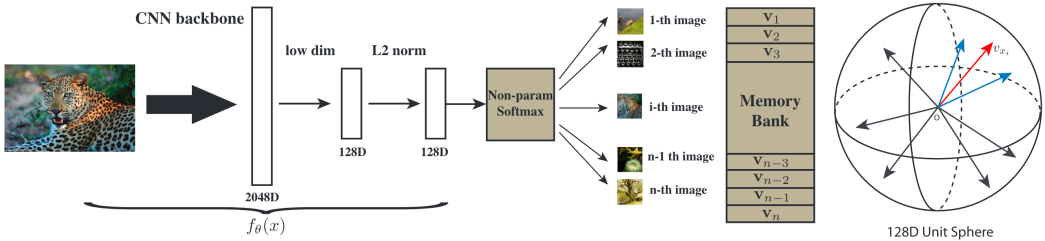
Reflection in Deep Learning

Example: Face verification



Source: Z Wu et al, 1805

InstDisc - 1805

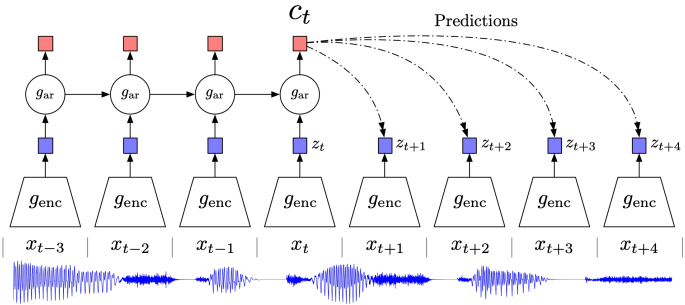


Source: Z Wu et al, 1805

New pretext task: Instance Discrimination Prior to MoCo

Non-Parametric SoftMax Classifier

CPC - 1807



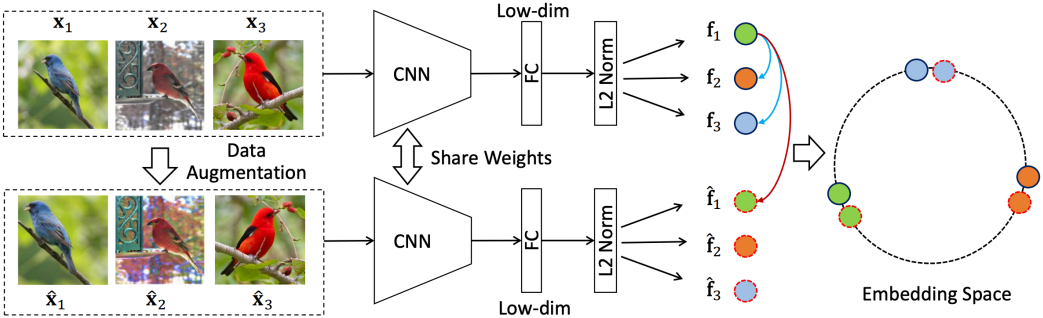
Source: A Oord et al, 1807

Prediction pretext task

Great applicability

Models: Encoder and autoregressive model

InvarSpread - 1904



Source: M Ye et al, 1904

Instance Discrimination

End-to-End without Memory Bank

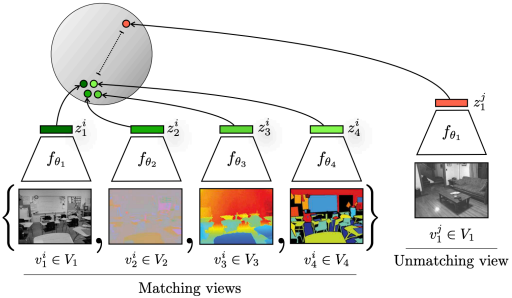
Only an encoder Prior to SimCLR

CMC - 1906

Humans view the world through many sensory channels. Each view is noisy and incomplete, but important factors are shared between all views.
Ex: a dog can be seen, heard, and felt.

Hope to find a powerful representation is one that **models view-invariant factors**.

Subsequent works: Clip (OpenAI), Knowledge Distillation, Muse.



Source: Y Tian et al, 1906
Different encoders to sense different signals.

Conclusion to Stage 1

Versatile Developments

- Different Pretext tasks
  - instance-level discrimination
  - Prediction
- Different Objective Function
  - NCE loss
  - Mutual Information
  - InfoNCE loss
- Different views in Positive/Negative Pairs - defined by pretext task

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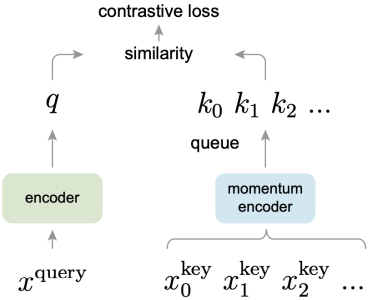
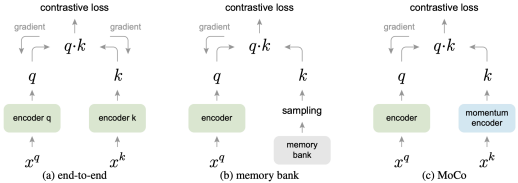
MoCo - 1911

Contrastive Learning can be viewed as dictionary lookup.

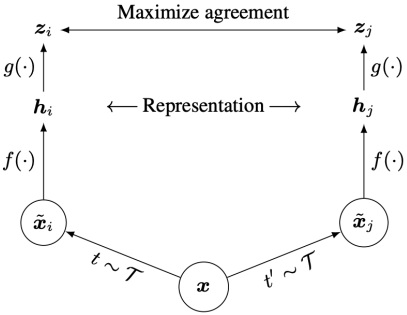


Source: K He et al, 1911



A desirable dictionaries should be
1. Large and 2. Consistent during training
Contributions: Dictionary and Momentum encoder

SimCLR - 2002



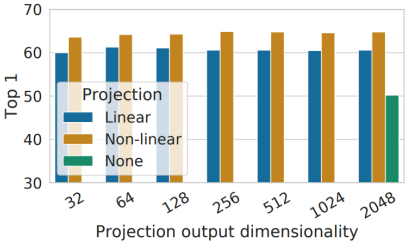
Source: T Chen et all, 2002

Contributions

More augmentations

Larger batch size and longer training time

Learnable nonlinear transformation



MoCo v2 - 2003 & SimCLR v2 - 2006

Updates

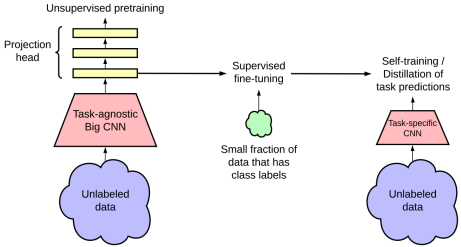
- More augmentations
- Project head

case	unsup. pre-train MLP	aug+	cos	epochs	batch	ImageNet acc.
MoCo v1 [6]				200	256	60.6
SimCLR [2]	✓	✓	✓	200	256	61.9
SimCLR [2]	✓	✓	✓	200	8192	66.6
MoCo v2	✓	✓	✓	200	256	**67.5**
*results of **longer** unsupervised training follow:*						
SimCLR [2]	✓	✓	✓	1000	4096	69.3
MoCo v2	✓	✓	✓	800	256	**71.1**

Source: X Chen et all, 2003

Updates

- Deeper ResNet
- Two hidden layer MLP
- Momentum encoder

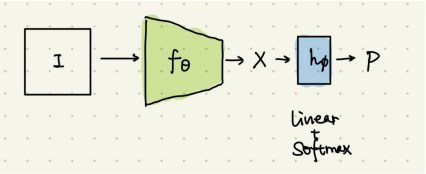


Source: T Chen et all, 2006

SeLa - 1911 & SwAV - 2006

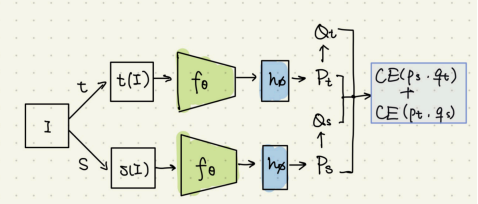
IDEA: Get an analytics solution of pseudo-label and use p to predict the pseudo-label.

q should be K-dimension determined by # of Clusters.



Ref: Y Asano et all, 1911

IDEA: Applied constrastive concept into the SeLa.



Ref: M Caron et all, 2006

Clustering SSL is similar to constrative loss

MoCo: 6w Negative v.s. 3k clusterings

Supervised: 76.5% v.s. SwAV: 75.3%

Trick: Mult-crop

Conclusion to Stage 2

Close to Unified Architecture

- Objective: InfoNCE-related
- Similar Architecture
  - Project head
  - Momentum encoder
  - Deeper backbone

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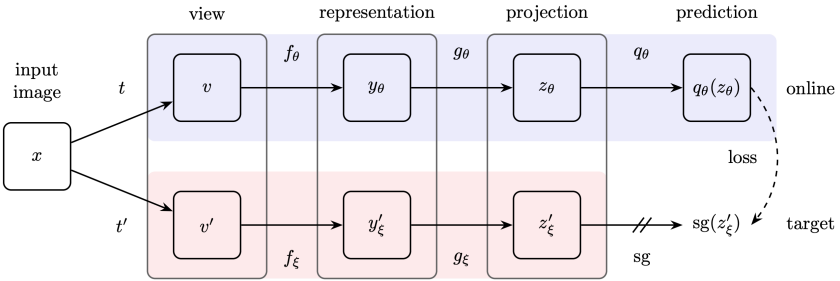
BYOL - 2006

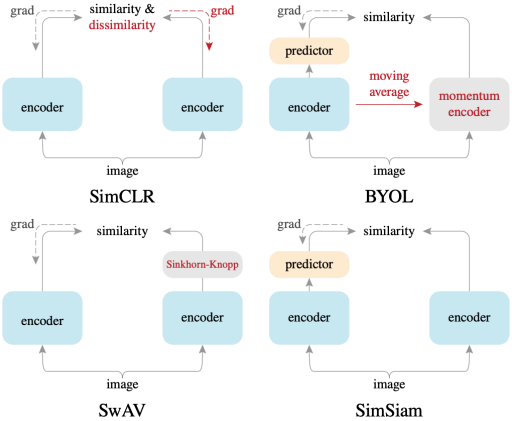


Source: J Grill et all, 2006

Combination of MoCo, SimCLR and SwAV.

Appply the MSE loss instead of InfoNCE.

SimSiam - 2011



Source: X Chen et all, 2011

IDEA: Applied constrastive concept into the SeLa.

method	batch size	negative pairs	momentum encoder	100 ep	200 ep	400 ep	800 ep
SimCLR (repro.+)	4096	✓		66.5	68.3	69.8	70.4
MoCo v2 (repro.+)	**256**	✓	✓	67.4	69.9	71.0	72.2
BYOL (repro.)	4096		✓	66.5	**70.6**	**73.2**	**74.3**
SwAV (repro.+)	4096			66.5	69.1	70.7	71.8
SimSiam	**256**			**68.1**	70.0	70.8	71.3

Why not collapse: stop gradient.

MoCo v3 - 2104 & DINO - 2104

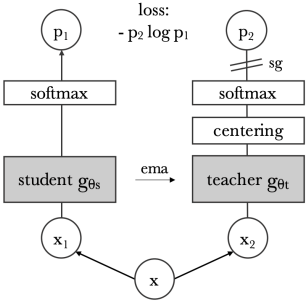
ViT bring a drastic technological changes, replace CNN with ViT

Algorithm 1 MoCo v3: PyTorch-like Pseudocode

```
# f_q: encoder: backbone + proj mlp + pred mlp
# f_k: momentum encoder: backbone + proj mlp
# m: momentum coefficient
# tau: temperature

for x in loader: # load a minibatch x with N samples
   x1, x2 = aug(x), aug(x) # augmentation
   q1, q2 = f_q(x1), f_q(x2) # queries: [N, C] each
   k1, k2 = f_k(x1), f_k(x2) # keys: [N, C] each

   loss = ctr(q1, k2) + ctr(q2, k1) # symmetrized
   loss.backward()

   update(f_q) # optimizer update: f_q
   f_k = m*f_k + (1-m)*f_q # momentum update: f_k

# contrastive loss
def ctr(q, k):
   logits = mm(q, k.t()) # [N, N] pairs
   labels = range(N) # positives are in diagonal
   loss = CrossEntropyLoss(logits/tau, labels)
   return 2 * tau * loss
```

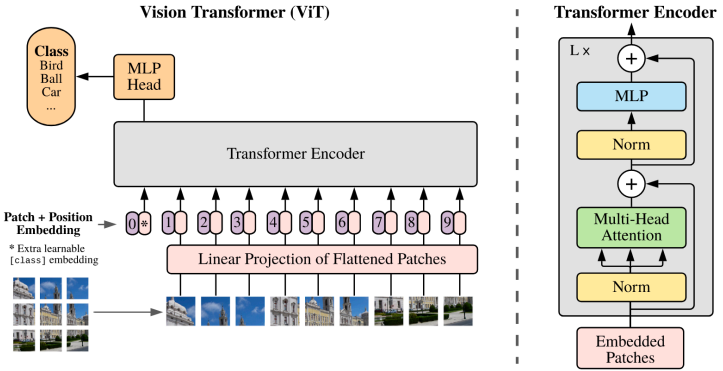
Notes: `mm` is matrix multiplication. `k.t()` is `k`'s transpose. The prediction head is excluded from `f_k` (and thus the momentum update).

Source: M Caron et all, 2006



Source: M Caron et all, 2104

ViT - 2010


Vision Transformer (ViT)
Class
Bird
Ball
Car
...
MLP Head
Transformer Encoder
Patch + Position Embedding
* Extra learnable [class] embedding
0* 1 2 3 4 5 6 7 8 9
Linear Projection of Flattened Patches
Transformer Encoder
L ×
MLP
Norm
Multi-Head Attention
Norm
Embedded Patches

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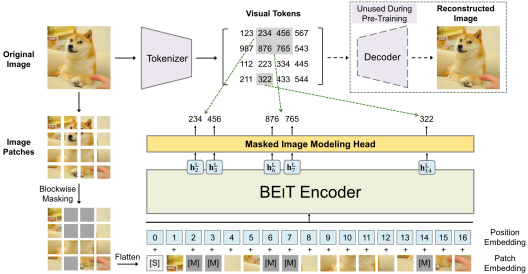
BEiT - 2106

Random masking some percentage of image patches, and then predict the discrete visual tokens corresponding to the masked patches.

Image patch & Visual token



Source: H Bao et al, 2106

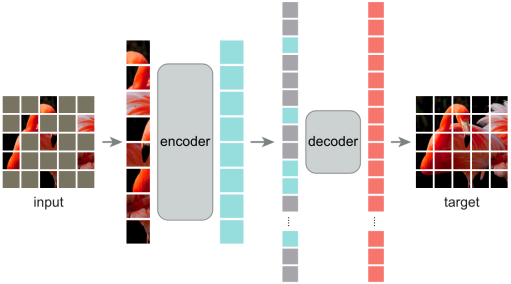
MAE - 2111

Random masking with a **high mask ratio**.

Encoder operate only on a small subset of all set.

Decoder: Full set of tokens consisting of (i) encoded visible patches, and (ii) mask tokens. Each mask token is a shared, learned vector.

Reconstruction target: MSE between the reconstructed and original images only on masked patches.

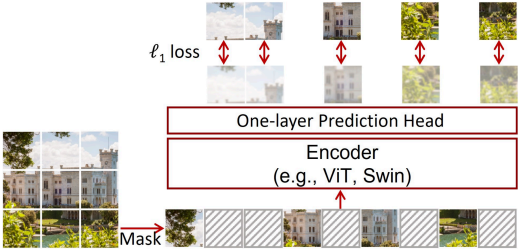


Source: K He et al, 2111

SimMIM - 2111

Observations

- Masking strategy: Random masking with relatively large patch size (eg. 32 $\times$ 32).
- Prediction heads: An extremely lightweight prediction head (linear layer).
- Prediction tragets: A simple raw pixel regression task.
- Encoder architecures: ViT, Swin and ResNet could all benefit from SimMIM.



Source: Z Xie et al, 2111