Photogrammetry & Robotics Lab Machine Learning for Robotics and Computer Vision Tutorial

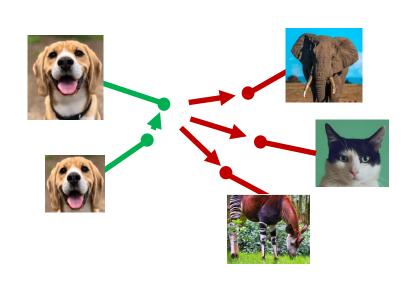
Pre-training & Self-supervision

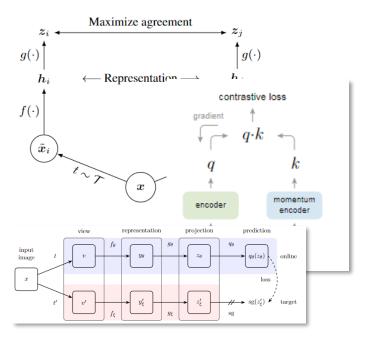
Jens Behley

Exam Dates

- Oral Exam via Zoom in English
- Webcam must be on all the time and alone in room
- No other windows besides Zoom open.
- Date from the voting: Wed, 25.08.2021
- If this date still doesn't fit, contact us and we provide one alternative date

This week's lecture



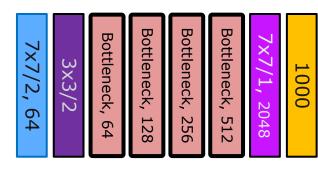


- Purely supervised training does not scale
- Using pre-trained models allows to get away with less labels!
- Self-supervised pretraining shows strong performance without any labels!

Pre-training & Fine-tuning

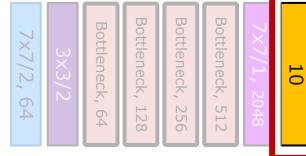
Stage 1: Pre-training (ImageNet)





Stage 2: Fine-tuning (Targeted dataset)





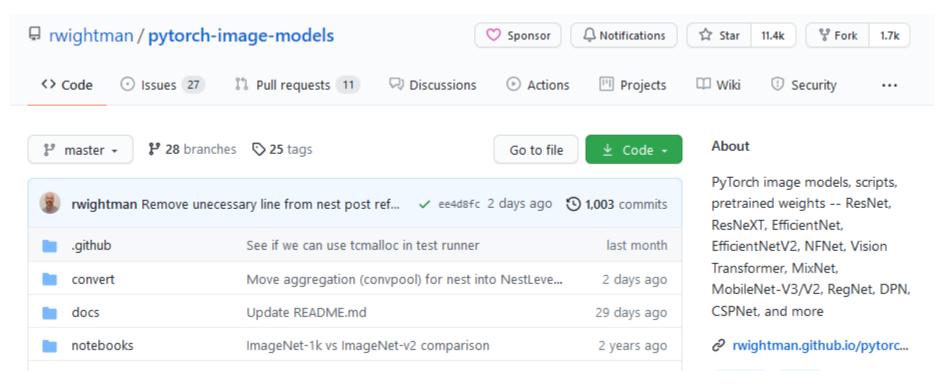
- Idea: Take weights from ImageNet and train only part of the network for novel task/dataset
- Training with pre-trained weights is faster and less data intensive!

Where to get pre-trained models?

 PyTorch vision contains pre-trained models for classification, segmentation, detection

Repository of other often contain pre-trained versions of their approach

Pytorch-image-models Repo



- Maintained by Ross Wightman
- Up-to-date implementation and pre-trained weights of state-of-the-art backbones
- 452(!) pretrained models/variants of common models

Feature Extraction

 The timm library provides handy methods to get just the features, see Docs: https://rwightman.github.io/pytorch-imagemodels/feature_extraction/

forward_features()

```
import torch
import timm

m = timm.create_model('xception41', pretrained=True)

o = m(torch.randn(2, 3, 299, 299))
print(f'Original shape: {o.shape}')

o = m.forward_features(torch.randn(2, 3, 299, 299))
print(f'Unpooled shape: {o.shape}')
```

Output:

```
Original shape: torch.Size([2, 1000])
Unpooled shape: torch.Size([2, 2048, 10, 10])
```

Other Domains or Modalities



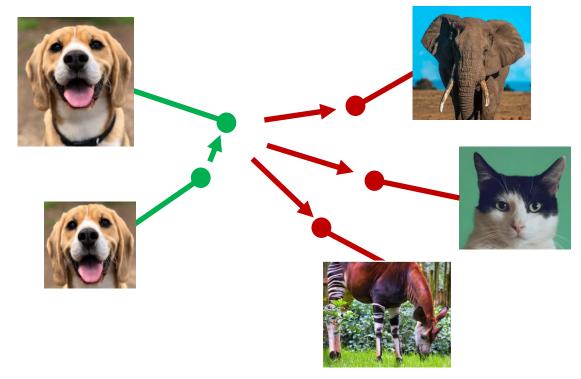






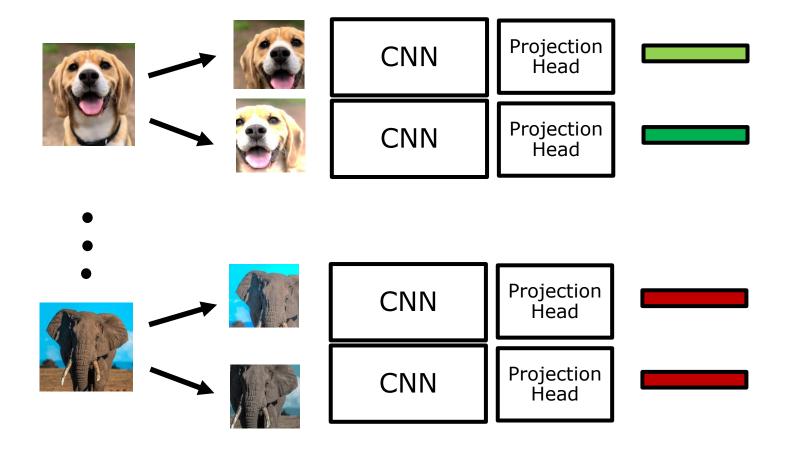
- ImageNet features or characteristics not always the best fit → Self-supervised Learning
- Specifically: Contrastive Learning

Contrastive Learning



 Idea: Learn representations such that similar examples (positives) are closer than representations of different examples (negatives)

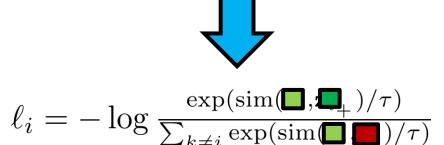
Common framework



Contrastive Loss

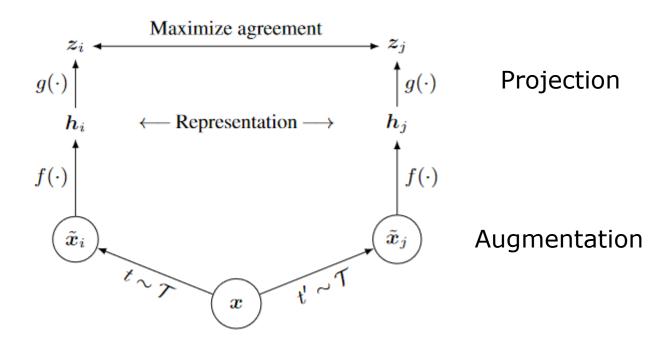
Temperature scaled contrastive loss:

$$\ell_i = -\log \frac{\exp(\operatorname{sim}(\mathbf{z}_i, \mathbf{z}_{i_+})/\tau)}{\sum_{k \neq i} \exp(\operatorname{sim}(\mathbf{z}_i, \mathbf{z}_k)/\tau)}$$



• Cosine Similarity: $sim(\mathbf{u}, \mathbf{v}) = \frac{\mathbf{u}^{\top} \mathbf{v}}{\|\mathbf{u}\| \|\mathbf{v}\|}$

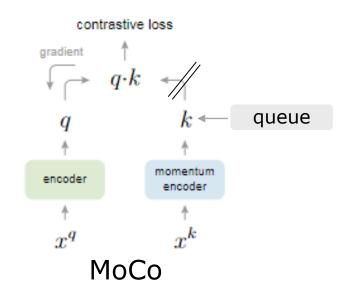
SimCLR



- Idea: Learn representations by finding agreement between projected features
- Compute contrastive loss over projections/latents z
- Projection $g(\cdot)$ via FC \rightarrow ReLU \rightarrow FC

[Chen, 2020] 12

Momentum Encoder

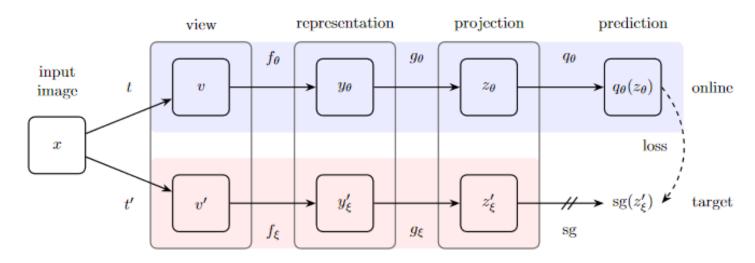


• Only updated with weighted average between parameters of encoder θ_q and parameters of momentum encoder θ_k :

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

Typically, large values (e.g., m = 0.999) better
 then smaller values (e.g., m = 0.9)
 [He, 2020]

Boostrap your own latent (BYOL)



- Augmented views are passed through online and target network
- Online network predicts output of the target network
- Important: There are no negative examples involved!

BYOL training and update

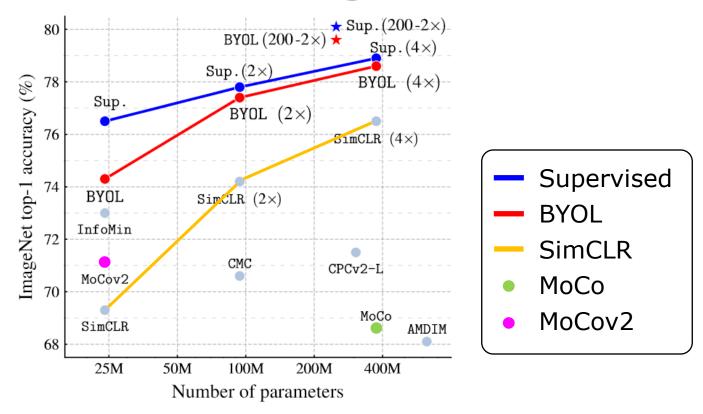
• Loss measures difference between prediction $q(z_{\theta})$ and output of target network z'_{ξ} :

$$\ell = \left\| \frac{q(z_{\theta})}{\|q(z_{\theta})\|_{2}} - \frac{z_{\xi}'}{\|z_{\xi}'\|_{2}} \right\|_{2}^{2} = 2 - 2 \cdot \frac{q(z_{\theta})^{\top} z_{\xi}'}{\|q(z_{\theta})\|_{2} \|z_{\xi}'\|_{2}}$$

- Only online network is directly updated via backpropagation
- Target network parameters ξ are updated via momentum:

$$\xi \leftarrow m\xi + (1-m)\theta$$

Comparison on ImageNet



- Results for ResNet50 with different widths (=number of channels), e.g., 2x, 4x
- BYOL approaches supervised training

See you next week!