Query Efficient Model Extraction with Self-Supervised Contrastive Learning

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Trustworthy Machine Learning

Introduction

- Extension of *High Accuracy and High Fidelity Extraction of Neural Networks* by *Jagielski et. al* - 2020
- **Attack Model**
  - Black Box access to our target model - we can access output scores
  - We have some unlabeled dataset representative of the target's input
  - Image classification task
- **Goal:**
  - Steal a copy of the target model with high-accuracy on the target's task
  - Do this with as few queries as possible using self-supervised learning
  - Original paper used Rotation Loss, which will serve as our baseline

Self-Supervised Contrastive Learning

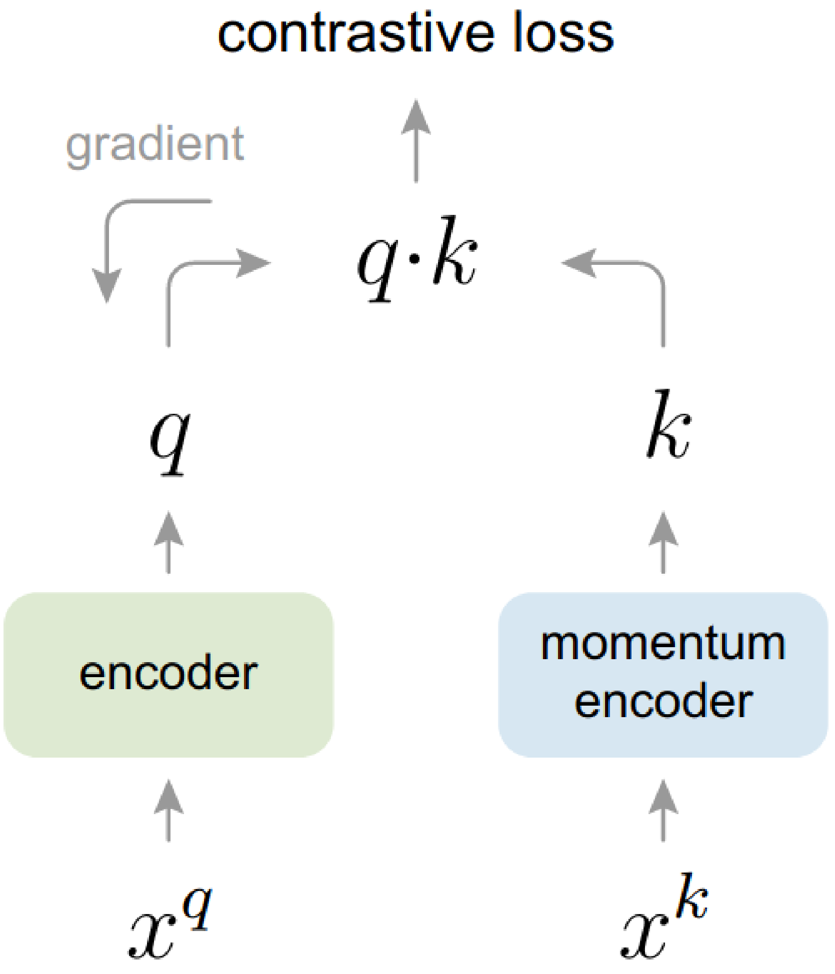
- Use some backbone network to embed images in an embedding space
- Images belonging to the same class should be more similar than images belonging to different classes
- We do not have label access in the self-supervised scenario, so we construct some pretext task to learn good embeddings
- For contrastive learning we generate two augmentations of an input image, and try to maximize their similarity in the embedding space
- Model collapse occurs when all images are embedded to a constant point

MoCo

- Each image gives two augmentations x^q and x^k
- Both encoders share the same model architecture
- Encoder weights (θ_q) updated by standard backpropogation
- Momentum encoder weights (θ_k) updated by:

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

  - $m \in [0, 1)$ is a hyperparameter

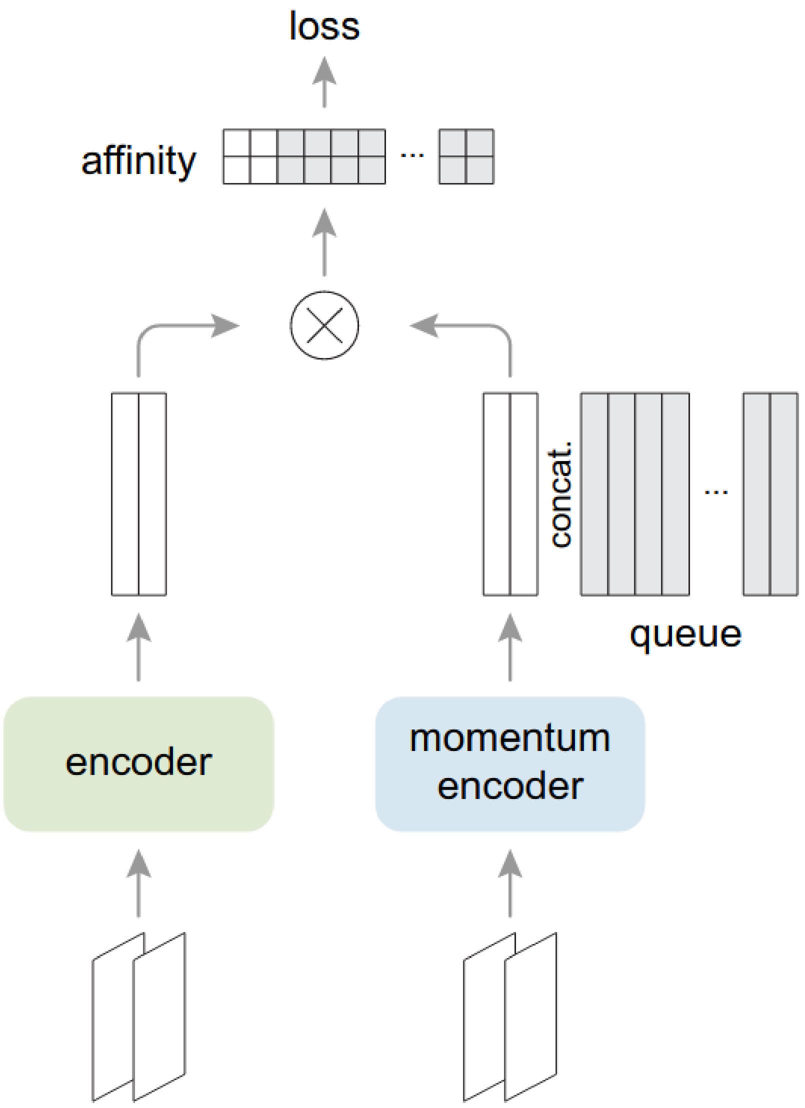


MoCo

- **Loss Function**

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

- q and k_+ correspond to the same image (positive pair)
- Model retains a queue (length K) of samples, such that we can reuse the encoded samples from previous batches (negative pairs)
- τ is a temperature hyperparameter



Momentum Contrast for Unsupervised Visual Representation Learning, He et al. - 2020

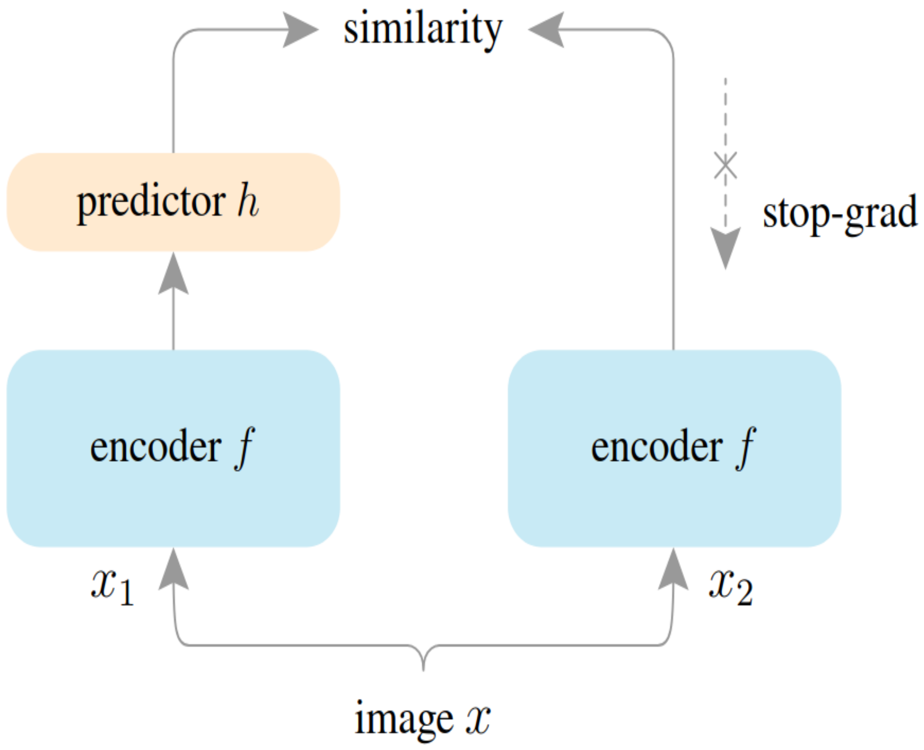
SimSiam

- Now the encoders share weights
- The predictor is a two layer MLP
- **Loss Function**

$$\mathcal{L} = \frac{1}{2}\mathcal{D}(p_1, z_2) + \frac{1}{2}\mathcal{D}(p_2, z_1)$$

$$\mathcal{D}(p_1, z_2) = -\frac{p_1}{||p_1||_2} \cdot \frac{z_2}{||z_2||_2}$$

- p is the predictor output, z is the RHS encoder output
- Encoder never receives gradients from z



Proposed Algorithm

1. Collect an initially unlabeled dataset (ImageNet)
2. Conduct self-supervised pretraining with the unlabeled data with our local model (ResNet-50)
3. Query the target model (ResNeXt-101) using some amount of the unlabeled data to obtain output scores
4. Add a single fully-connected classification layer to the local model (encoder for MoCo) and finetune using the target's output scores in a distillation approach

- We are interested in how the self-supervised pre-training step impacts performance versus training only with our queried data

Training Specifics

- **Pretraining**
  - Follow the procedure in each method's corresponding paper
- **Finetuning for 1% and 10% Data Fractions**
  - For finetuning after pretraining follow the procedure outlined in *Prototypical Contrastive Learning of Unsupervised Representations, Li et al.*
    - 20 epochs, different classifier/ResNet learning rates
  - For finetuning without pretraining follow the procedure outlined in *S4L: Self-Supervised Semi-Supervised Learning, Zhai et al.*
    - 1000 (1%) or 200 (10%) epochs
- **100% Data Training**
  - Follow the default pytorch ImageNet training protocol
    - 90 epochs

Results

Top-1/Top-5 Accuracy

Data Fraction	Supervised*	Rotation*	MoCo	SimSiam
1%	8.20/23.25	17.11/40.92	**39.35/68.99**	16.84/40.24
10%	55.25/80.37	52.37/79.04	**61.05/85.03**	53.40/79.49
100%	76.00/92.99	X	**76.72/93.35**	X

* - Baselines

- Supervised has no pre-training, we train directly on 1%/10% of the data.
- Our target model has 84.2/97.2 accuracy on ImageNet

Conclusions

- We see a clear improvement over the supervised baseline and previous self-supervised work with model extraction
- We can combine self-supervised training with additional query-efficient techniques to further improve model extraction
- More specific training protocols may have to be implemented to get the most out of finetuning
- SimSiam performs better than MoCo for other tasks, however MoCo clearly outperforms it here