Deep Learning for Computer Vision

Self-Supervised Learning

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Unsupervised Learning

Clustering

Group the data into clusters to reveal something meaningful about the data

Dimensionality Reduction

Learn low-dimensional representations of data that are meaningful for a given task

Data Generation

Learn to generate data belonging to a given training distribution

Representation Learning

Learn a distribution that implicitly reveals data representation that helps a downstream task

Unsupervised Learning

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Learn low-dimensional representations of data that are meaningful for a given task

Data Generation

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Representation Learning

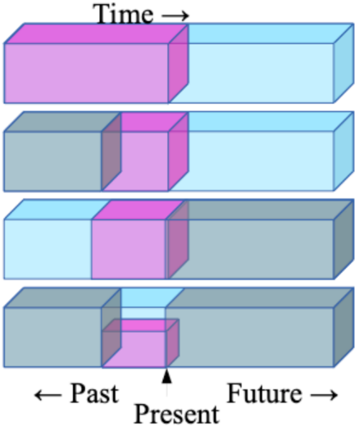
Learn a distribution that implicitly reveals data representation that helps a downstream task
$\rightarrow$ **Self-Supervised Learning**!

What is Self-Supervised Learning?

- Exploit unlabeled data to yield labels
- Design supervised tasks (called **pretext/auxilliary tasks**) that can learn meaningful representations for downstream tasks
- Analogous to filling in the blanks: predict certain part of input from any other part

Self-Supervised Learning

- Predict any part of the input from any other part.
- Predict the future from the past.
- Predict the future from the recent past.
- Predict the past from the present.
- Predict the top from the bottom.
- Predict the occluded from the visible
- **Pretend there is a part of the input you don't know and predict that.**

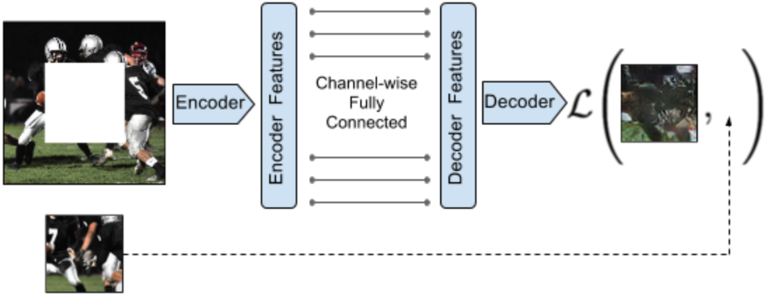


Credit: Yann LeCun

Why Self-Supervised Learning?

- Deep supervised learning works well when labeled data is abundant
- There is a plethora of unlabeled data available; how can we exploit it?
- Humans don't always need supervision to learn, we learn by observation and prediction

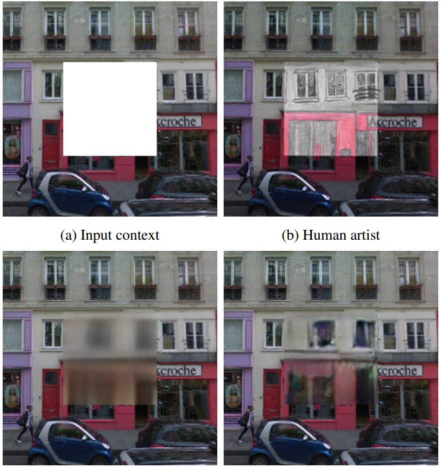
Self-Supervision In Computer Vision: Image Inpainting[1]



- **Context autoencoder** trained to fill in missing parts of an image
- Mask of missing region could be of any shape
- Encoder derived from Alexnet architecture
- Model trained with a combination of L2 loss and adversarial loss

[1] Pathak et al, Context Encoders: Feature Learning by Inpainting, CVPR 2016

Self-Supervision In Computer Vision: Image Inpainting[2]



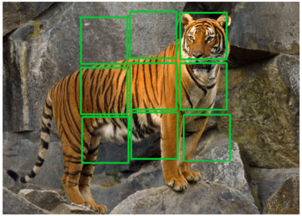
(a) Input context (b) Human artist

(c) Context Encoder ($L2$ loss) (d) Context Encoder ($L2$ + Adversarial loss)

[2]Pathak et al, Context Encoders: Feature Learning by Inpainting, CVPR 2016

Learning Image Representation by Solving Jigsaws[3]

- Used to teach a model that object is made of different parts
- Learns feature mapping of object parts and their spatial arrangement by solving a 9-tiled jigsaw puzzle



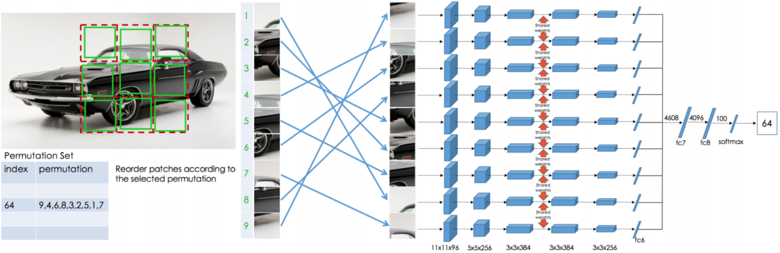
(a)

(b)

[3] Noroozi and Favaro, Unsupervised Learning of Visual Representations by Solving Jigsaw Puzzles, ECCV 2016

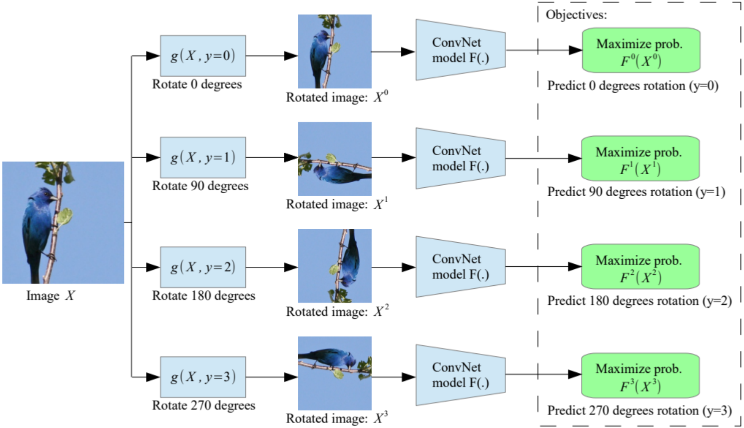
Learning Image Representation by Solving Jigsaws[4]

- 9 tiles shuffled via a randomly chosen permutation from predefined permutation set are fed to network
- Predicts index of permutation applied
- Output vector gives probability of permutation indices used
- Cross entropy loss used for training



[4] Noroozi and Favaro, Unsupervised Learning of Visual Representations by Solving Jigsaw Puzzles, ECCV 2016

Representation Learning by Predicting Rotations[5]



Learns high level object concepts such as their location in the image, their type, their pose etc.

[5]Gidaris et al, Unsupervised Representation Learning by Predicting Image Rotations, ICLR 2018

Representation Learning by Predicting Rotations[6]

- K rotations are applied, and model outputs a probability distribution over all rotations
- Log loss is used for training
- Loss for an image X is given by:

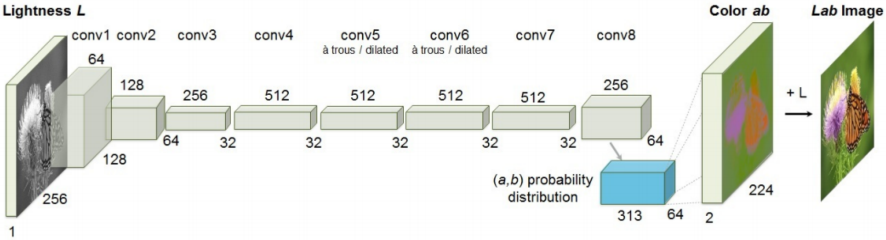
$$\mathcal{L}(X, \theta) = -\frac{1}{K} \Sigma_{y=1}^{K} \log(F(g(X|y)|\theta))$$

$g(\cdot|y)$ is the y^{th} transformation function, F denotes the ConvNet

[6] Gidaris et al, Unsupervised Representation Learning by Predicting Image Rotations, ICLR 2018

Image Colorization[7]

- Predicts color of a grayscale input image in LAB space
- Maps image to a distribution over 313 AB pairs of quantized color value outputs



Cross-entropy loss of predicted probability distribution over binned color values used to train the network

[7]Zhang et al, Colorful Image Colorization, ECCV 2016

Contrastive Learning-Based SSL

- Learns representations by contrasting positive and negative samples; goal is to learn an encoder f such that:

$$score(f(x), f(x^+)) >> score(f(x), f(x^-))$$

x^+ obtained from same image as x and x^- dissimilar to x; scores given by cosine similarity

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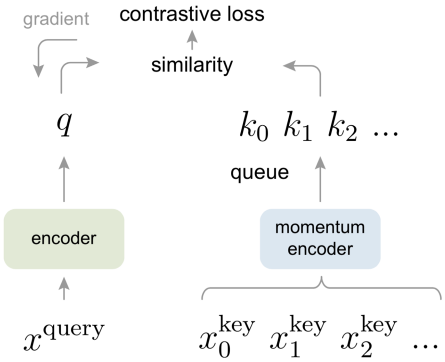
- General form of loss function given by:

$$\mathcal{L} = -\mathbb{E}\left[\log \frac{\exp(score(f(x), f(x^+))/\tau)}{\exp(score(f(x), f(x^+))/\tau) + \Sigma_{j=1}^{N-1} \exp(score(f(x), f(x_j^-))/\tau)}\right]$$

  where τ is temperature hyperparameter

MoCO: Momentum Contrast[8]



- Proposes unsupervised learning of visual representations as a **dynamic dictionary look-up**

[8]He et al, Momentum Contrast for Unsupervised Visual Representation Learning, CVPR 2020

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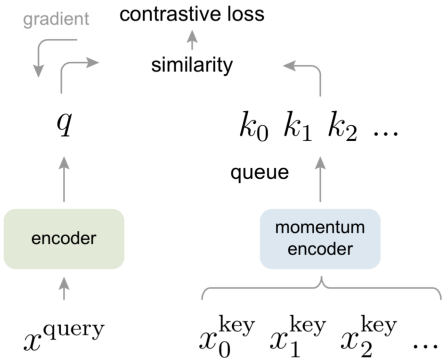

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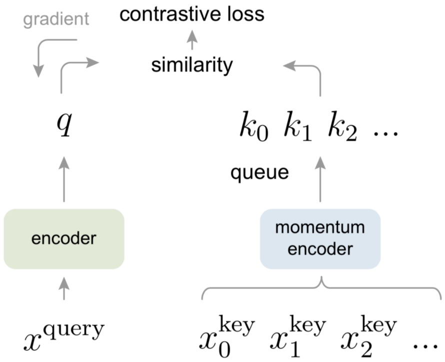

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- Given query sample x_q, query representation obtained using an encoder $q = f_q(x_q)$

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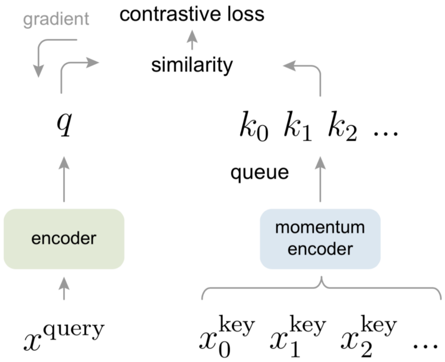

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- Given query sample x_q, query representation obtained using an encoder $q = f_q(x_q)$
- Key samples encoded by a momentum encoder $k_i = f_k(x_{k_i})$ gives a set of key representations: $\{k_1, k_2, \cdots\}$ in dictionary

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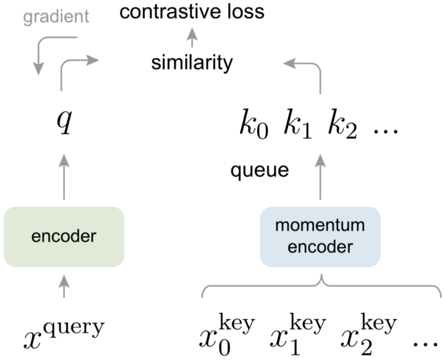

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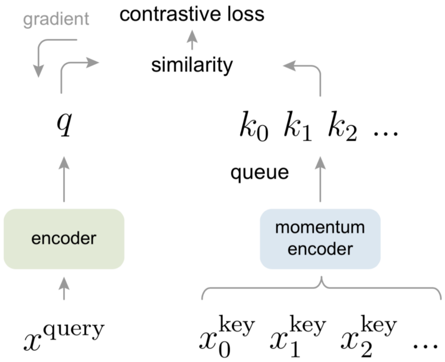

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- Loss on previous slide (contrastive loss) used to learn

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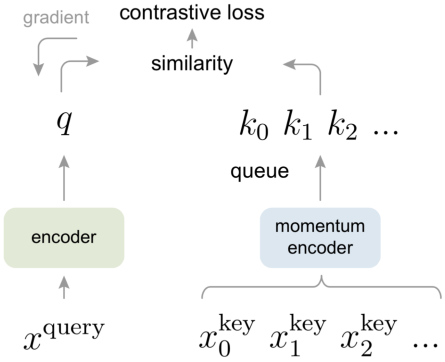
MoCO: Momentum Contrast[9]

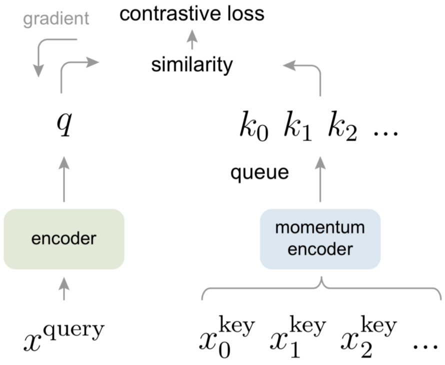


Momentum Contrast

- Query and key encoders both updated based on loss
- Maintains dictionary as queue of data samples
- Allows reuse of encoded keys from immediate preceding mini-batches, decouples dictionary size from batch size
- **Momentum-based update** proposed to keep keys approximately consistent

[9] He et al, Momentum Contrast for Unsupervised Visual Representation Learning, CVPR 2020

MoCO: Momentum Contrast[10]



Momentum Contrast

- Using queue as dictionary makes it difficult to update key encoder
- Can we just copy the key encoder from the query encoder?

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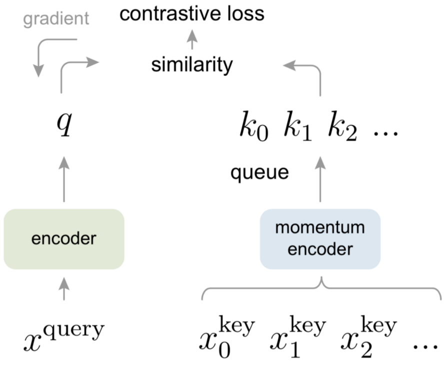


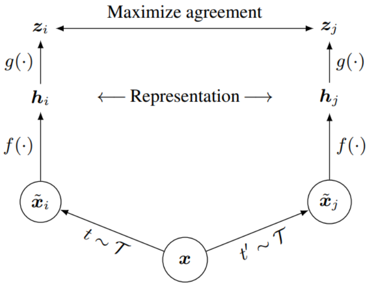
Momentum Contrast

- Using queue as dictionary makes it difficult to update key encoder
- Can we just copy the key encoder from the query encoder? (No! Representation will not be consistent because of rapidly changing query encoder)
- Query encoder (f_q) is updated using backpropagation and key encoder (f_k) is updated using momentum as:

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

[10] He et al, Momentum Contrast for Unsupervised Visual Representation Learning, CVPR 2020

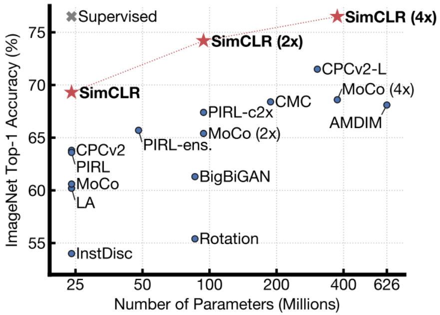
SimCLR: A Simple Framework for Contrastive Learning of Visual Representations[11]



- Learns via maximizing agreement between differently augmented views of same data example in latent space
- Given n images, $2n$ samples obtained by 2 different augmentations. Given one positive pair, there exist $2(n-1)$ negative pairs
- Loss operates on top of an extra projection of the representation via $g(.)$

[11] Chen et al, A Simple Framework for Contrastive Learning of Visual Representations, ICML 2020

SimCLR vs MoCo[12]



- **SimCLR Advantages:** Strong data augmentation techniques, MLP projection over the representations

[12] Chen et al, Improved Baselines with Momentum Contrastive Learning, arXiv 2020

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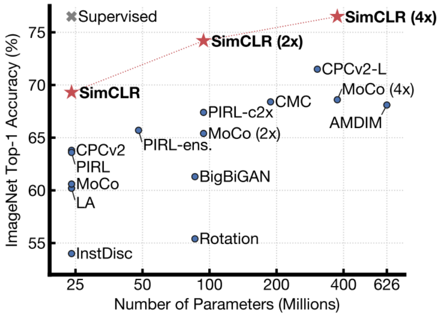

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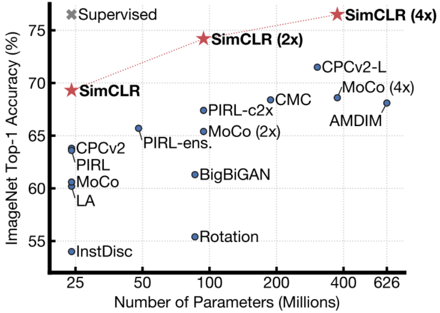

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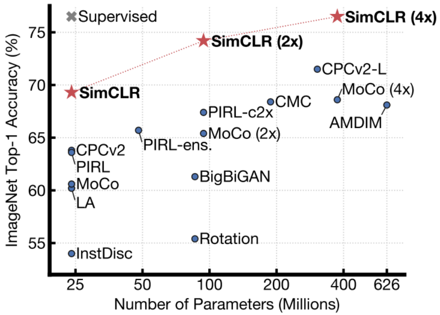

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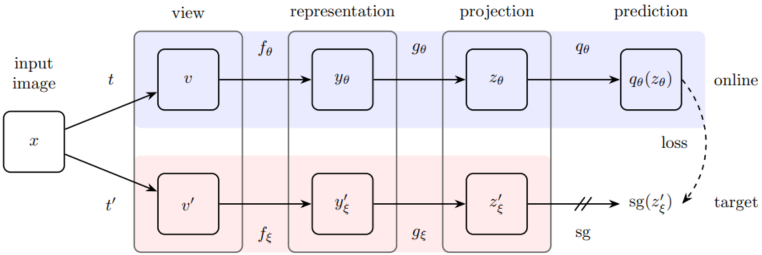
- **MoCo Advantage:** Decouples the batch size from the number of negatives
- Chen et al combined advantages from these two methods in MoCoV2

[12]Chen et al, Improved Baselines with Momentum Contrastive Learning, arXiv 2020

Bootstrap your Own Latent (BYOL)[13]



- Claims to achieve state-of-the-art results without dependency on negative samples

[13] Grill et al, Bootstrap Your Own Latent: A New Approach to Self-Supervised Learning, arXiv 2020

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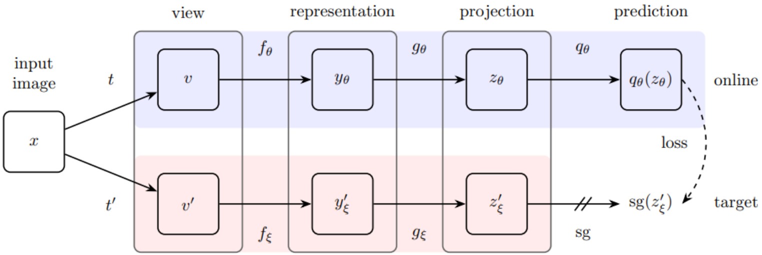

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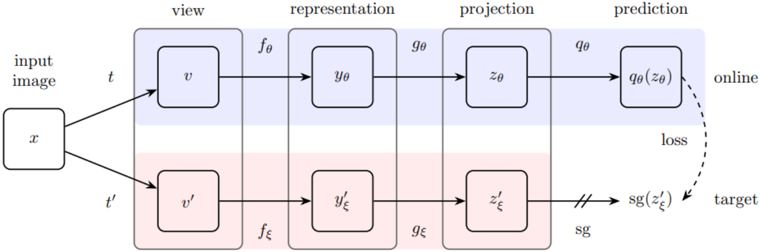

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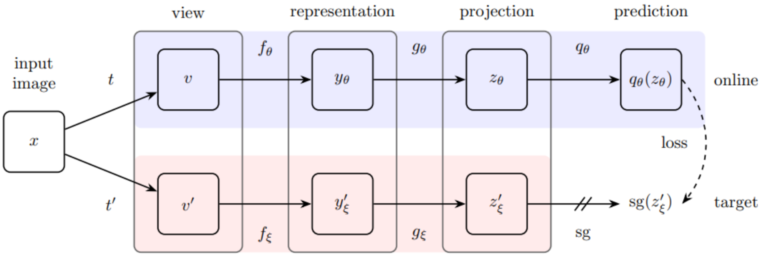

- Claims to achieve state-of-the-art results without dependency on negative samples
- Bootstraps outputs of a network to serve as targets
- Two networks: **online** and **target**, interact and learn from each other
- Online network predicts target network's representation of another augmented view of same image

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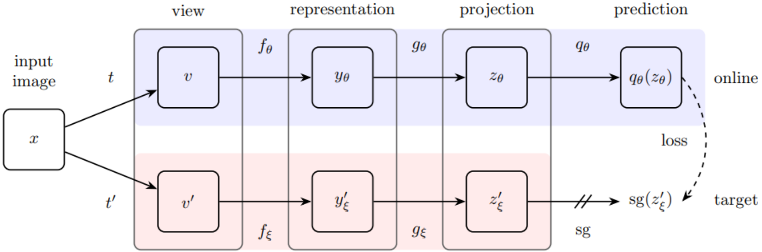
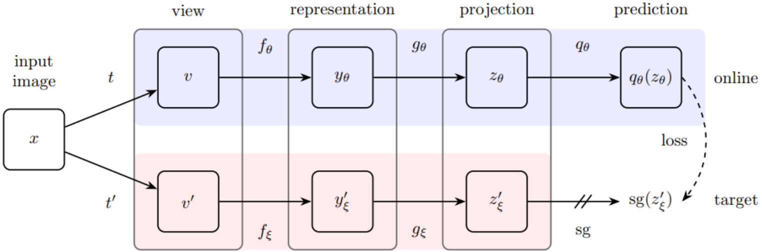
Bootstrap your Own Latent (BYOL)[14]



- $\mathcal{L}_\theta^{BYOL} = \|\bar{q}_\theta(z_\theta) - \bar{z}'_\xi\|_2^2$

[14]Grill et al, Bootstrap Your Own Latent: A New Approach to Self-Supervised Learning, arXiv 2020

Bootstrap your Own Latent (BYOL)[14]



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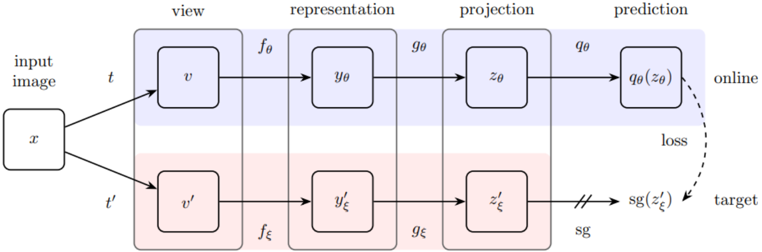

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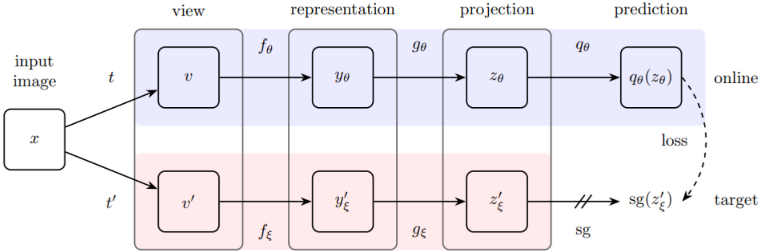

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- **Final Loss:** $\mathcal{L}_{final} = \mathcal{L}_\theta^{BYOL} + \bar{\mathcal{L}}_\theta^{BYOL}$

[14] Grill et al, Bootstrap Your Own Latent: A New Approach to Self-Supervised Learning, arXiv 2020

Homework

Readings

- Lilian Weng, Self-Supervised Representation Learning

References I

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References II

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