Lecture 13 Self-Supervised Learning

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1 Generative vs Self-supervised Learning

Both aim to learn from data without manual label annotation.
Generative learning aims to model data distribution pdata(x), e.g., generating realistic images.
Self-supervised learning methods solve pretext tasks that produce good features for downstream tasks.
Learn with supervised learning objectives, e.g., classification, regression.
Labels of these pretext tasks are generated automatically

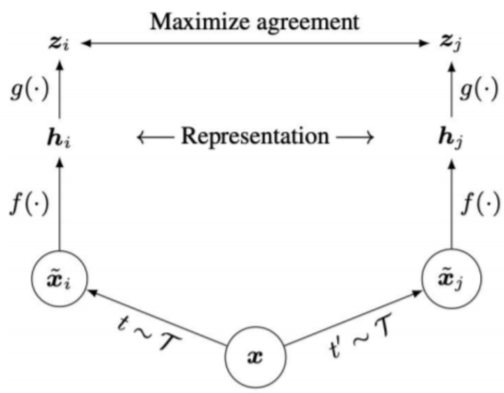
2 Pretext tasks from image transformation

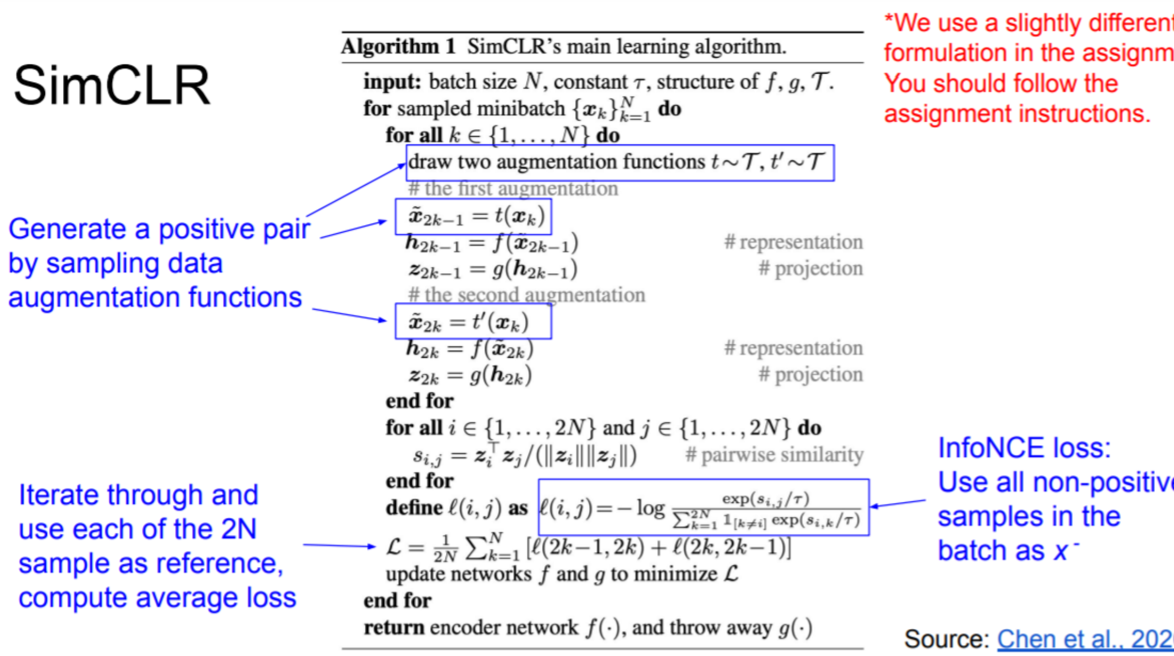
Predict rotations:
Predict relative patch locations:
Solve jigsaw puzzles:
Predict missing pixels:
Image coloring:Idea: cross-channel predictions.
Video coloring: Idea: model the temporal coherence of colors in videos.
Main method :
1, Context based
2,Temporal Based
3,Contrastive Based

3 Contrastive representation learning

Give a reference score: we want : $score(f(x), f(x^+)) >> score(f(x), f(x^-)$
x reference sample;
x^+ positive sample;
x^- negative sample;
Given a chosen score function, we aim to learn an encoder function f that yields high score for positive pairs $(x, x^+)$and low scores for negative pairs(x, x^-).

SimCLR:





Generate two similar image from one sample and minimize the difference between them.
Generate positive samples through augmentation: copping, color distortion, blur.
Use cos function as the score.($s_{i,j}$ in the picture)
Extra non-linear projection improve the representation learning. Why? Use h to do downstream works.

Momentum Contrastive Learning (MoCo)

Main operation: Dictionary as a queue,Momentum update,Shuffling BN.
Dictionary as a queue: Keep a running queue of keys, update after every epoch.
Momentum update: $\theta_k < -m\theta_k + (1-m)\theta_q$
Shuffling BN:
Now we have MoCov2 an MoCov3.
Above we based on positive and negative instances.

Contrastive Predictive Coding(CPC) (Base on sequential/temporal orders) mainly videos:
1. Encode all samples in a sequence into vectors $z_t = g_{enc}(x_t)$
2. Summarize context into a context code c_t using an auto-regressive model (g_{ar})
3. Compute InfoNCE loss between the context c_t and future code z_{t+k}using the following time-dependent score function: $s_k(z_{t+k}W_kc_t) = z_{t+k}^tW_kc_t$, where Wk is a trainable matrix.(use c_t to predict future z_{t+k} to test if c_t is good enough)