Contrastive Learning

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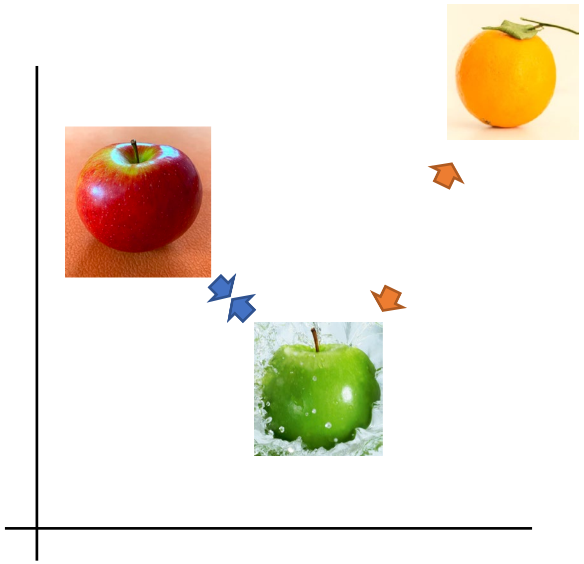
Lehrprobe Pattern Recognition



Lecture slides & materials

Course Context

Foto von Oleksandr Pidvalnyi von Pexels
https://www.pexels.com/de-de/foto/grune-und-graue-schere-2831794/

- Lecture “Deep Learning” or “Representation Learning”

- Semester 4+

- Prerequisites & prior knowledge:
  - Basic principles of machine learning, classification and regression
  - Multilayer perceptrons & convolutional neural networks
  - Loss functions, optimization and training of NNs
  - Initialization of (deep) neural networks

Embedding

Last week: General concepts of representation learning

This week: Contrastive learning

- **Recap**: Motivation & general concept of representation learning
- Generative vs. discriminative self-supervised learning
- Foundations of contrastive learning
- Recent approaches in contrastive learning
- Contrastive learning outside of computer vision
- Beyond contrastive: Non-contrastive learning
- Tricks-of-the-trade
- Applications
- Outlook and open research questions

Goals for Today

You will be able to …

- summarize the general concept of contrastive learning
- explain triplet loss as a fundamental technique
- identify recent advanced techniques for contrastive learning
- discuss strengths and weaknesses

… and you will know where to find more information

Motivation & Recap

- Supervised learning is ~~data~~ label-hungry
- Large amount of "unlabeled" data available

5B-Image-Question:

How can we utilize this data independent of the original task?

Adapted from: http://karpathy.github.io/2014/09/02/what-i-learned-from-competing-against-a-convnet-on-imagenet/

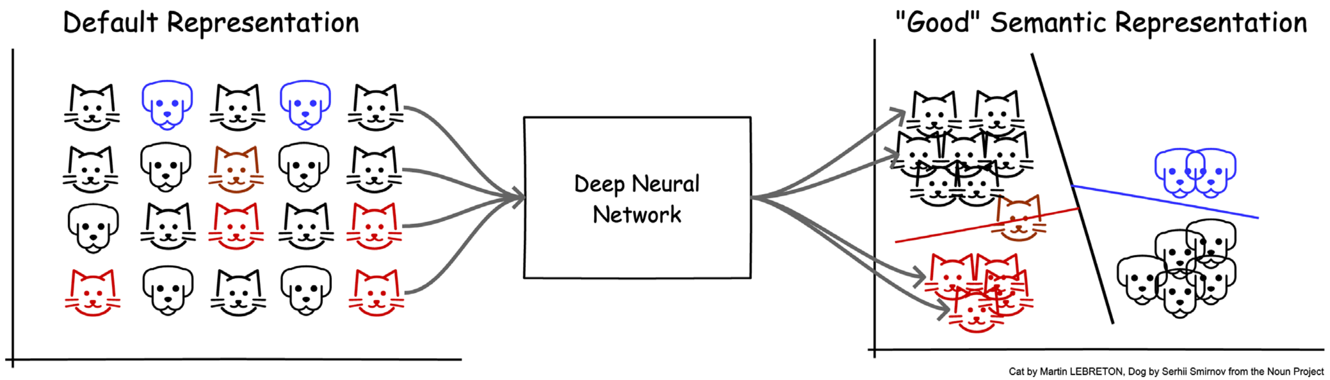
Source: https://laion.ai/blog/laion-5b/

Motivation & Recap (cont.)


Sources: https://www.shelma.eu/orig-image/82fc9d0584.jpg

- Pixel intensities are **bad representations** – for ML

- Approach:
  1. Train without labels to find "better" representations
  2. Solve subsequent task "easily" with (little) labeled data



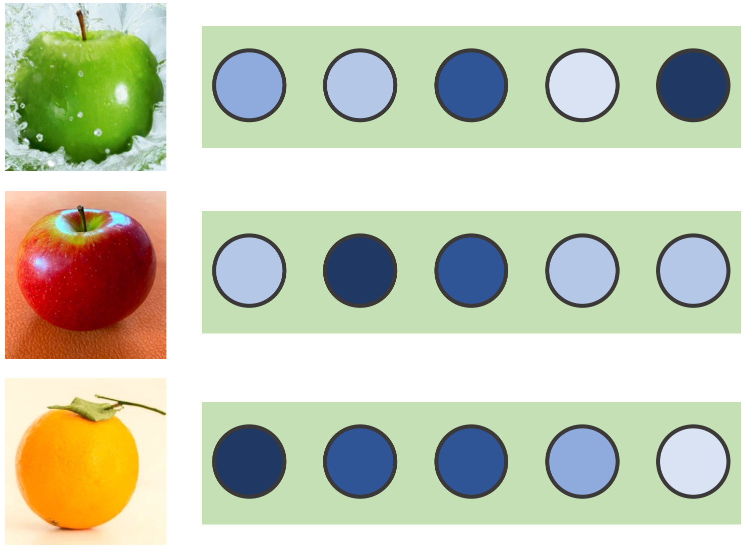
Source: https://blog.fastforwardlabs.com/2020/11/15/representation-learning-101-for-software-engineers.html

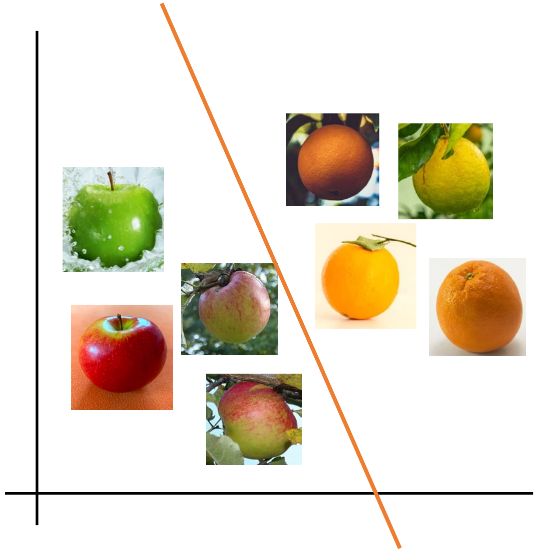
- Core questions:
  - What is the objective & loss function? → must be derived from the data itself
  - What is "better" & "easy"?

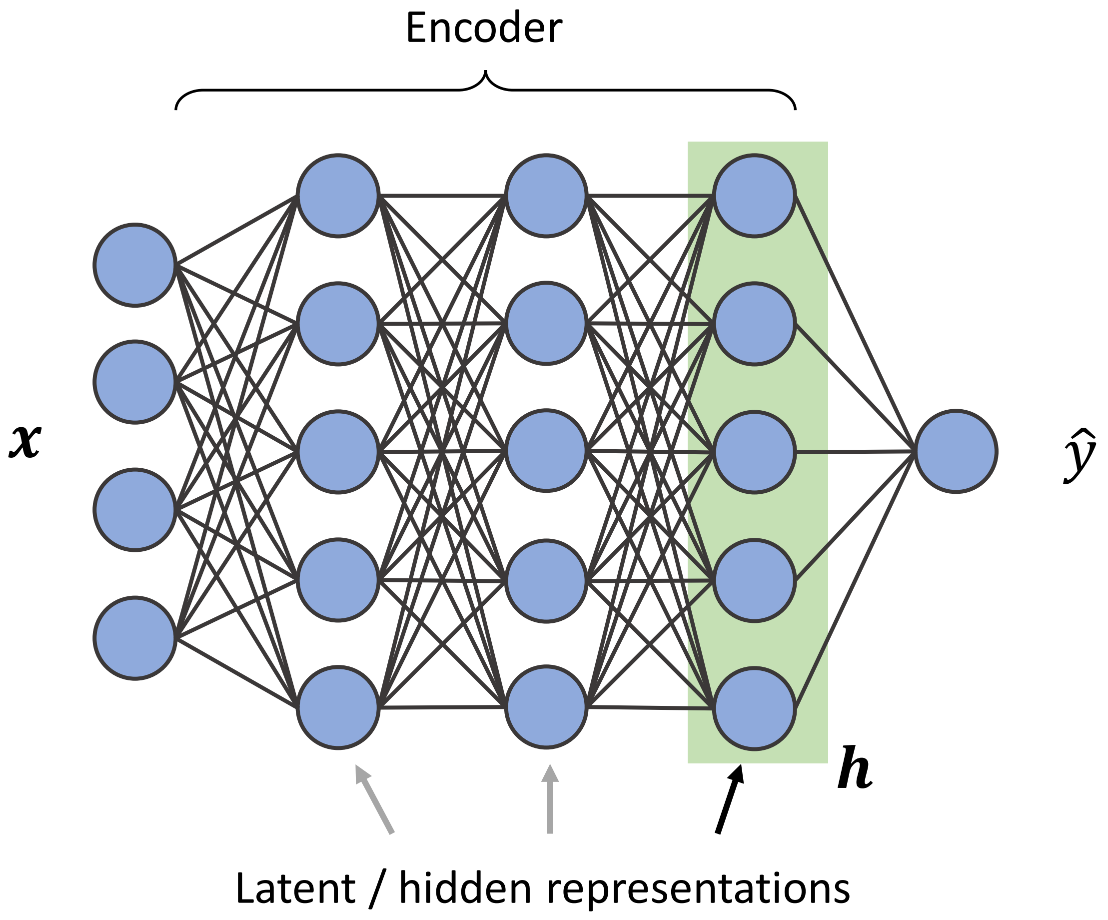
Foundations of Contrastive Learning

Supervised learning:

- Update weights to minimize $\mathrm{L}(\hat{y}, y)$
- Layers represent transformation chain



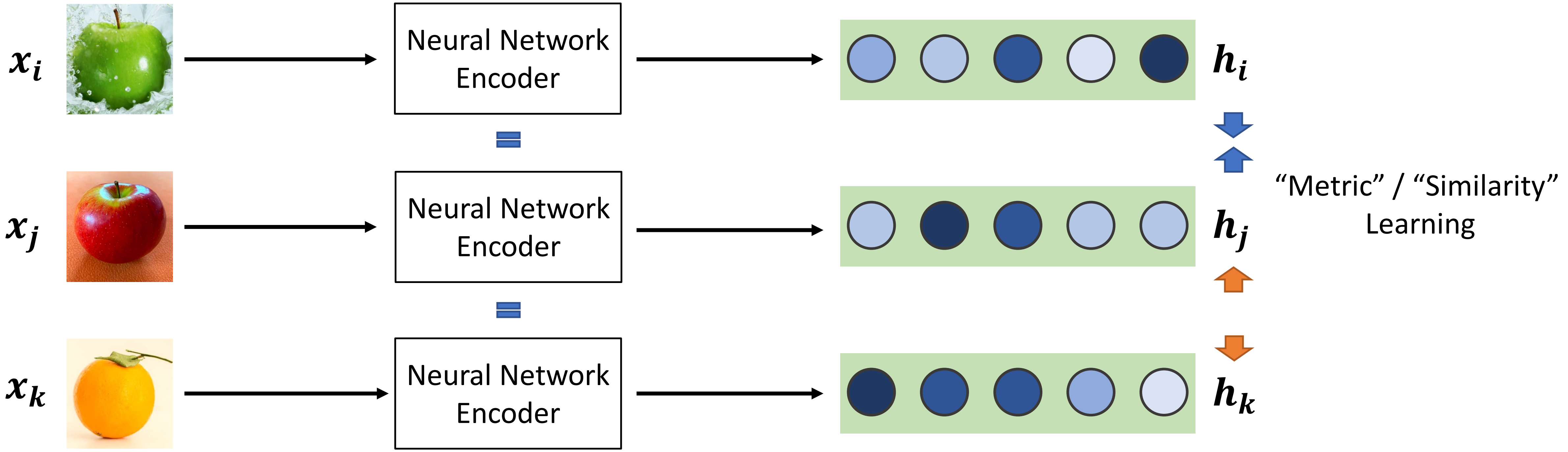




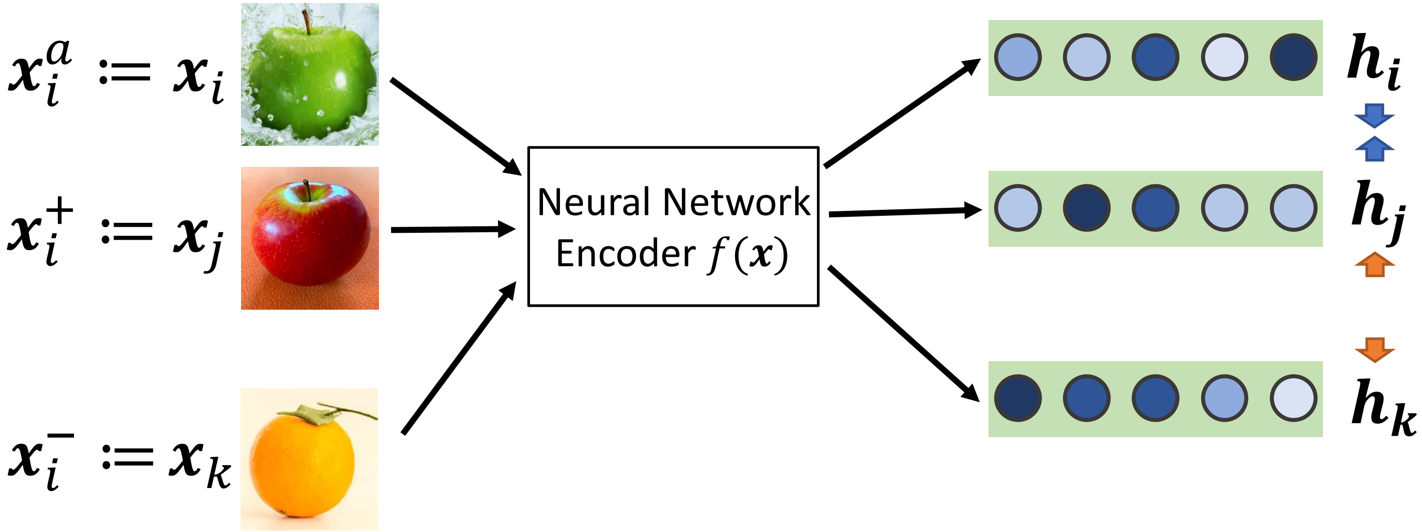
→ Implicit representation learning

Foundations of Contrastive Learning (cont.)

Supervised contrastive learning:



Triplet Loss [1]



- **Goal**: Maximize similarity of similar instances, minimize similarity of unrelated instances
- **Idea**:
  For anchor $\boldsymbol{x}_i^a := \boldsymbol{x}_i$, use negative and positive samples

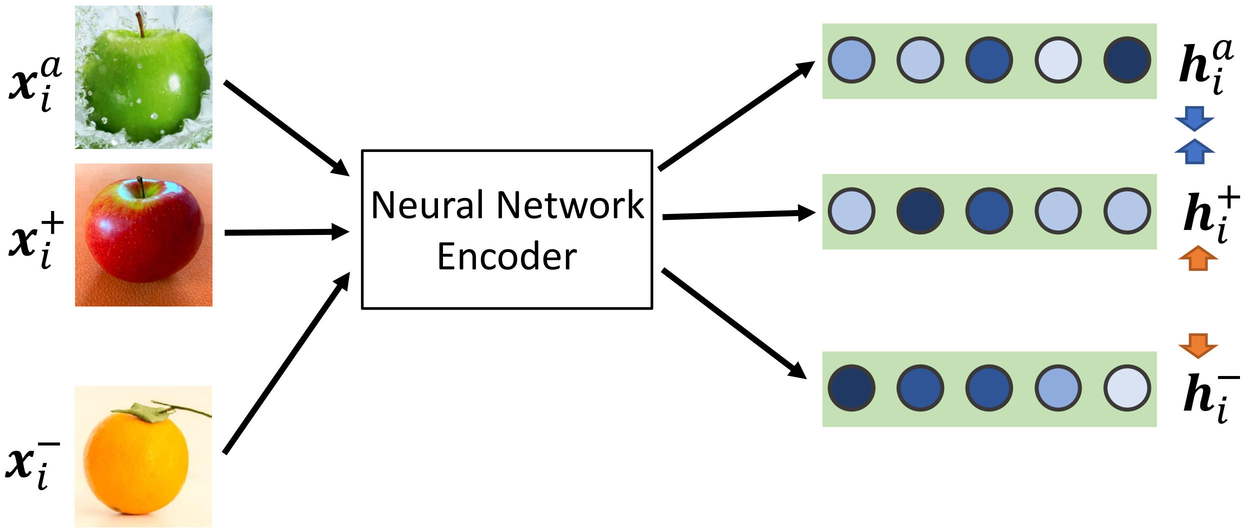
$$L(\boldsymbol{x}_i^a, \boldsymbol{x}_i^+, \boldsymbol{x}_i^-) =$$

- Additional trick: focus on “hard positive” and “hard negative samples”

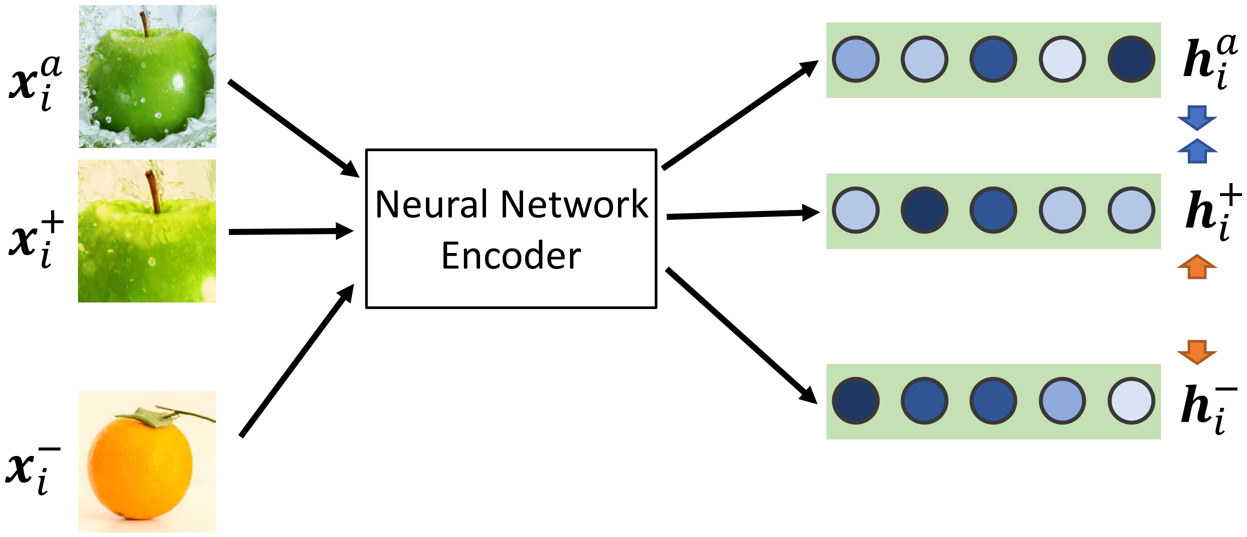
[1] Schroff, F., Kalenichenko, D., & Philbin, J. (2015). FaceNet: A unified embedding for face recognition and clustering. In: Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition 2015 (pp. 815-823).

Foundations of Contrastive Learning

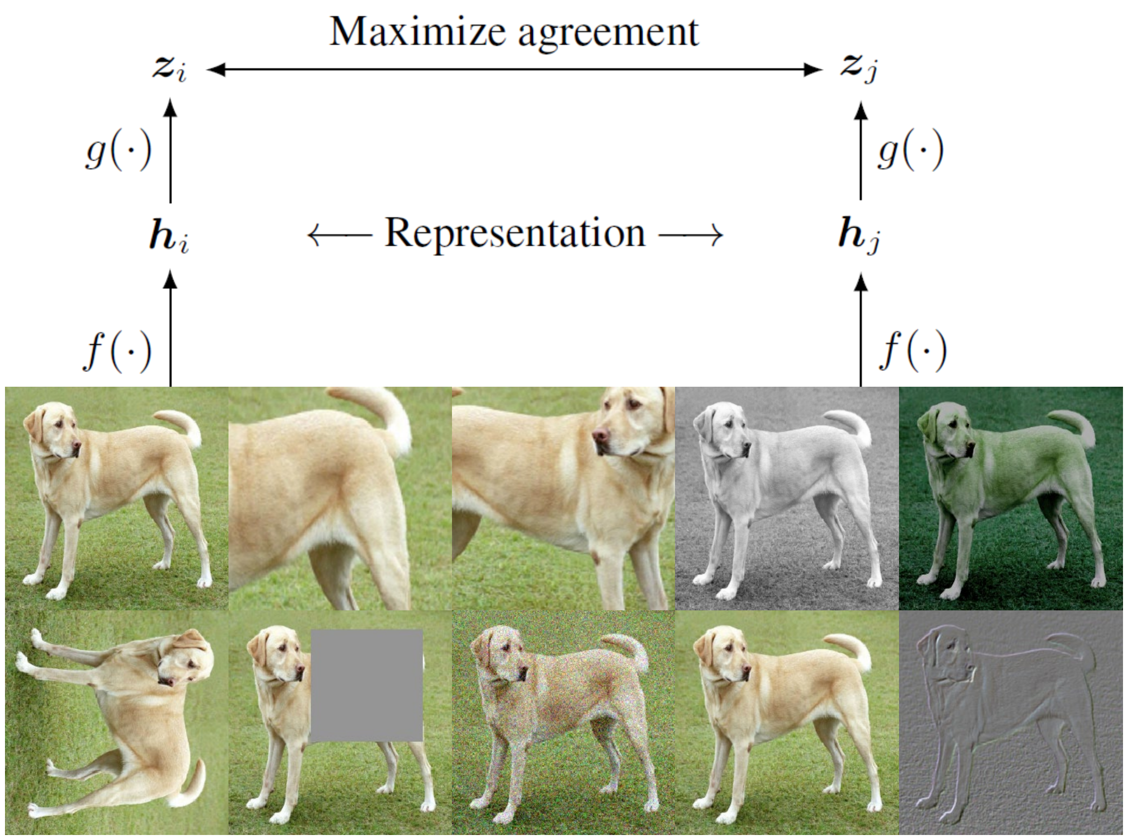
Supervised contrastive learning:



Unsupervised contrastive learning:



SimCLR – A simple framework for contrastive learning of visual representations [2]

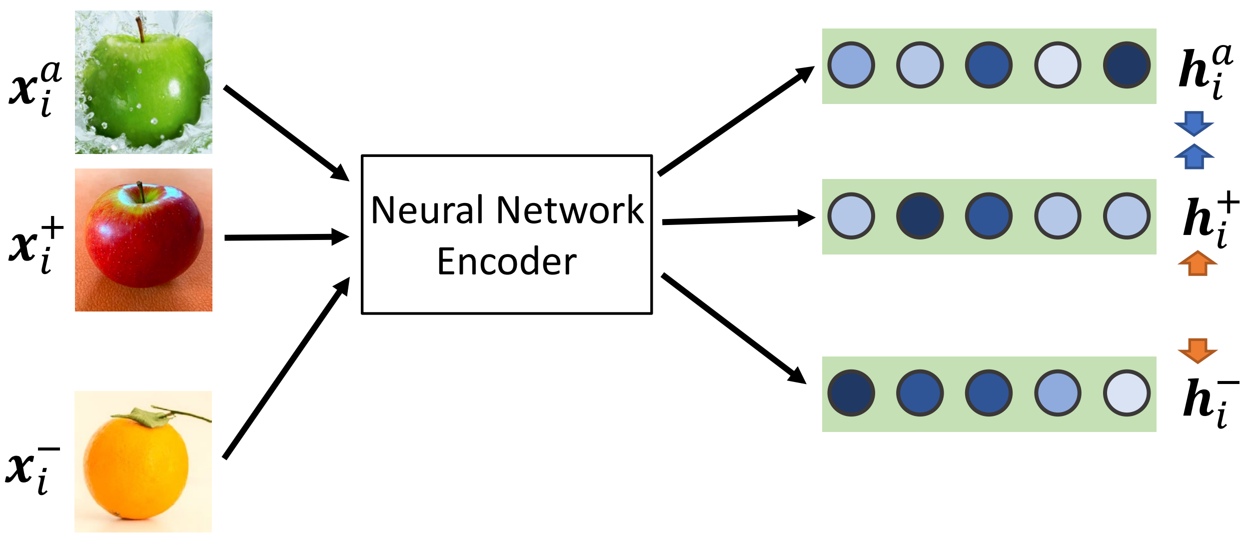


- Batch of samples,
  each sample augmented twice
  - Augmentations of the same sample as positive pairs
  - All other (augmented) samples are negative pairs
- Uses NT-Xtent Loss*
- Additional trick: projection head

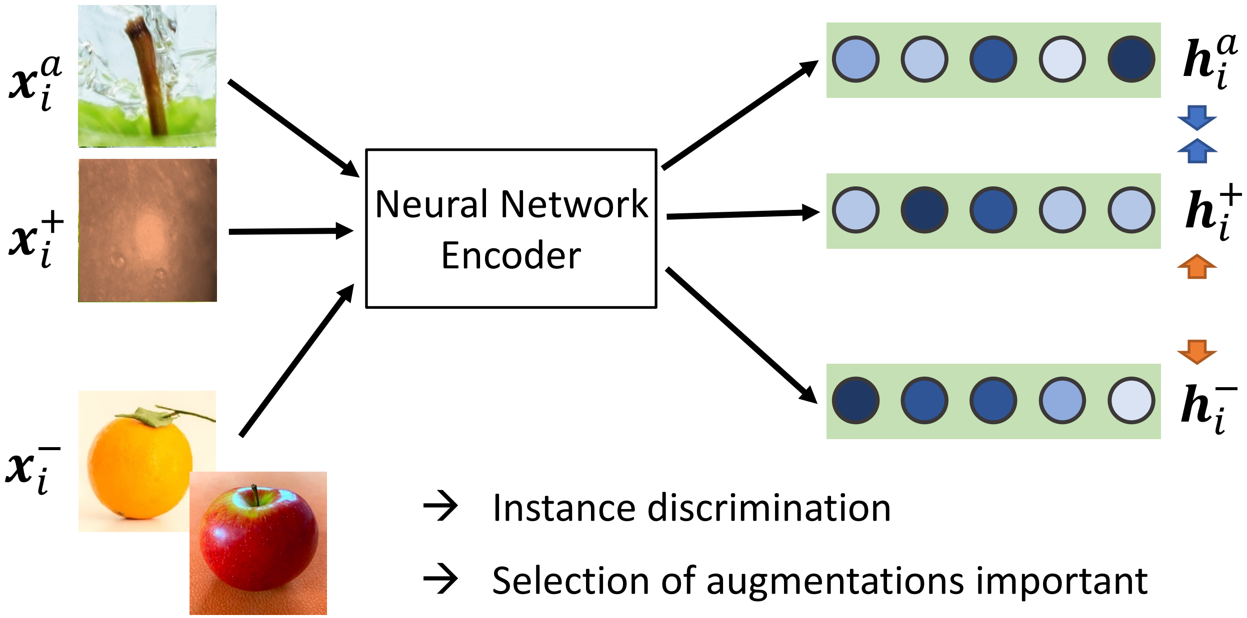
[2] Chen T., Kornblith S., Norouzi M., Hinton G., "A Simple Framework for Contrastive Learning of Visual Representations," In Proceedings of the 37th International Conference on Machine Learning (ICML 2020).

Challenges for Contrastive Learning

Supervised contrastive learning:



Unsupervised contrastive learning:

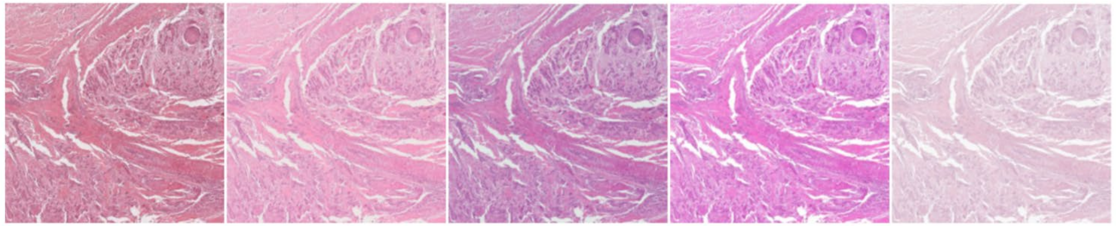


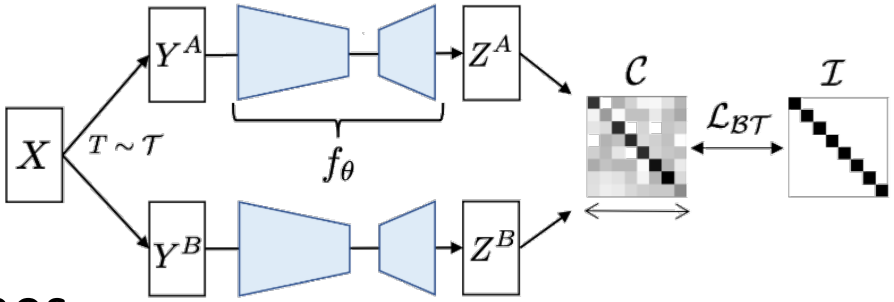
→ Instance discrimination

→ Selection of augmentations important

→ Global vs. local & whole vs. parts

Beyond Contrastive Learning





- Non-contrastive Learning:
  working with positive samples only
    - Barlow Twins [3]
    - SimSiam [4]
    - BYOL [5]

- Generative (pretext), adversarial & hybrid approaches
    - Inpainting, puzzle-solving, multi-modal learning
    - Domain adversarial learning

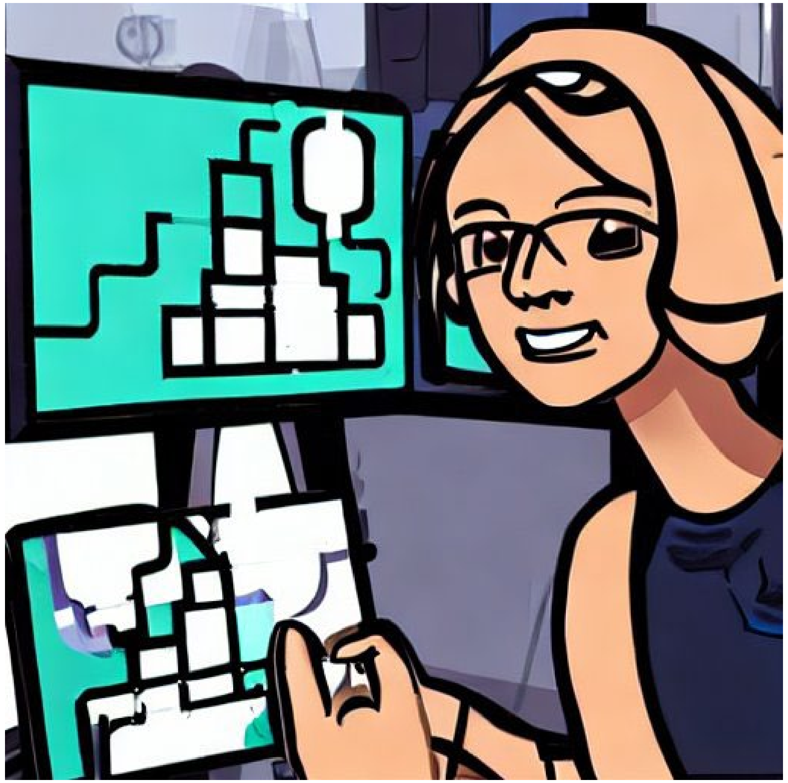
[3] Zbontar J., Jing L., Misra I., LeCun Y., Deny S., Barlow Twins: Self-Supervised Learning via Redundancy Reduction. Proceedings ICML, 2021.
[4] Chen X., He K., Exploring Simple Siamese Representation Learning. Proceedings of the IEEE/CVF CVPR, 2021.
[5] Grill J.-B., et al., Bootstrap your own latent: A new approach to self-supervised Learning. Advances in NeurIPS 33, 2020.

Summary and Outlook

- Contrastive learning has the goal to focus on representation, independent of downstream task
- Core concept: “Similar” inputs should have similar representations
  → contrastive & non-contrastive losses
- Open questions include:
  - How to fine-tune? What to transfer for different tasks?
  - Unification of approaches
  - Causality

Exercise/Homework (2 weeks)

- Extend classification & segmentation framework with contrastive loss, triplet loss & SimCLR
- Investigate learning behavior during contrastive learning
- Investigate convergence for downstream tasks
  - Binary classification
  - Many-class classification
  - Segmentation



< a female AI researcher playing with an AI, in comic style >

Thank you!

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