Deep Learning

Self-supervised Learning

Technische Hochschule Rosenheim
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Acknowledgements

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https://lme.tf.fau.de/

Supervised Learning

- We have seen impressive results achieved with…
  - large amounts of training data and
  - consistent, high-quality annotations.

Mask R-CNN image source [MAT19]

The Cost of Annotation

Image-level class labels: ~27 sec

Instance spotting: +14 sec

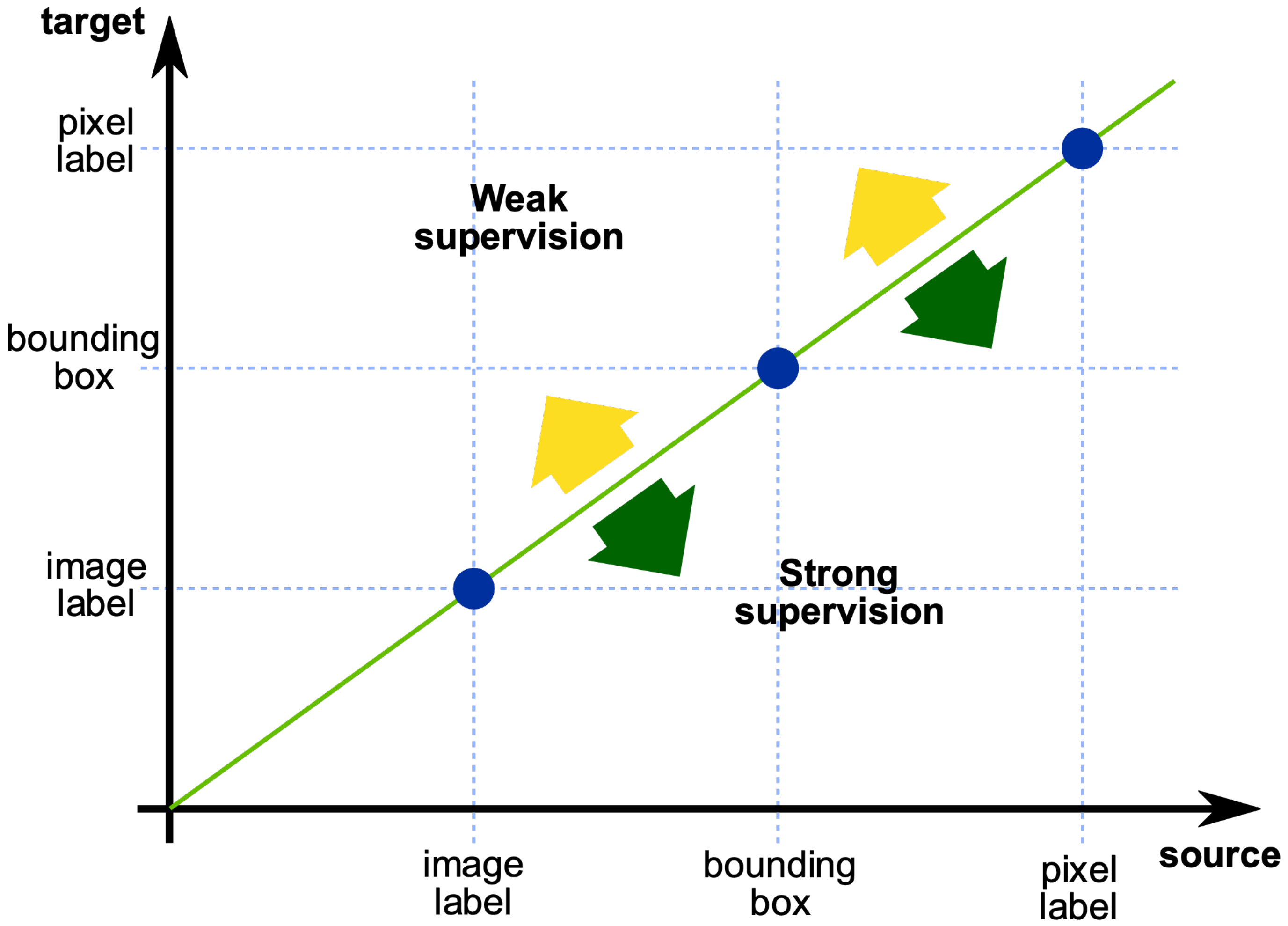
Instance Segmentation: +80 sec

Source: [Lin14]

Dense pixel-level annotations: 1.5h

Source: [Cor16]

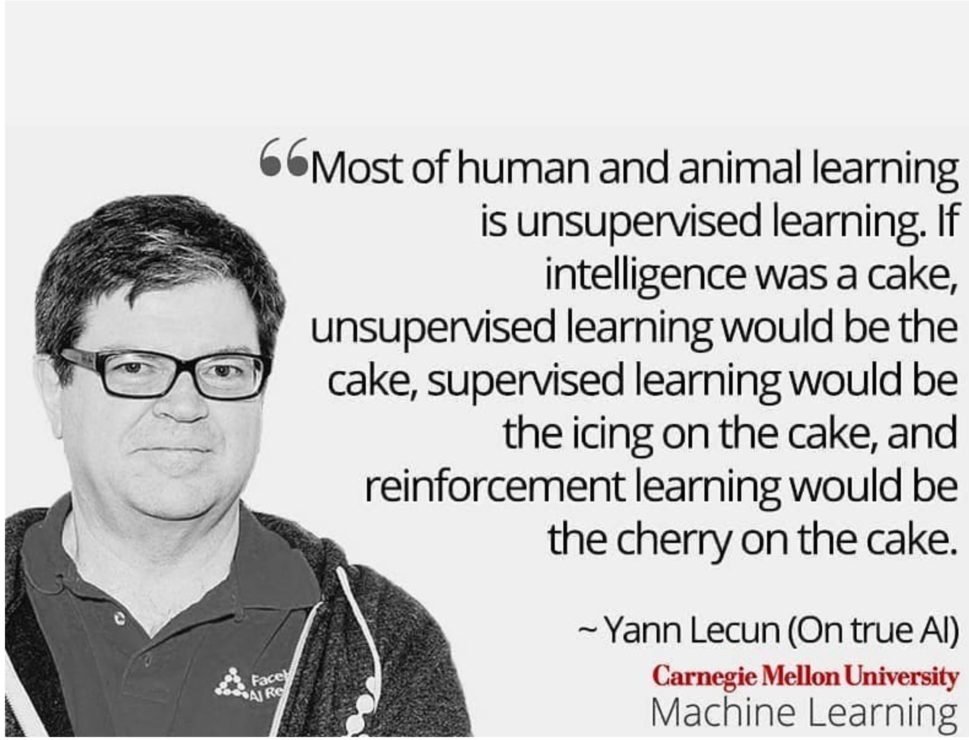
Strongly vs Weakly Supervised Learning



Reproduced from CVPR18 Tutorial: Weakly Supervised Learning for Computer Vision

Self-supervised Learning – Motivation

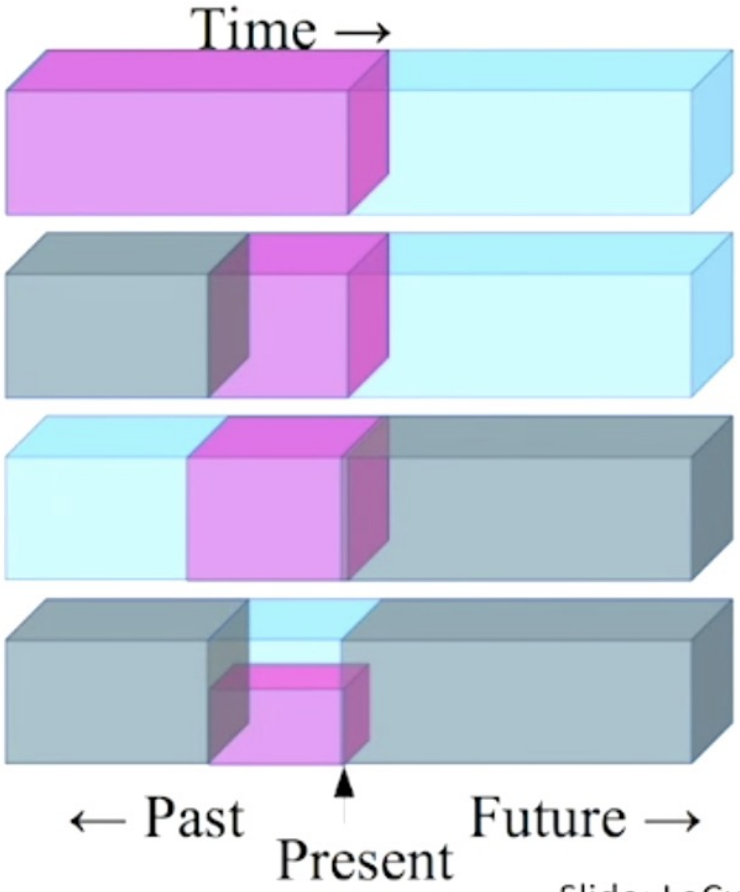
- Jitendra Malik: “Supervision is the opium of the AI researcher”
- Alyosha Efros: “The AI revolution will not be supervised”
- Yann LeCun:



Source: https://www.facebook.com/722677142/posts/10156036317282143/

Self-supervised Learning – Idea

- 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.



Slide: LeCun

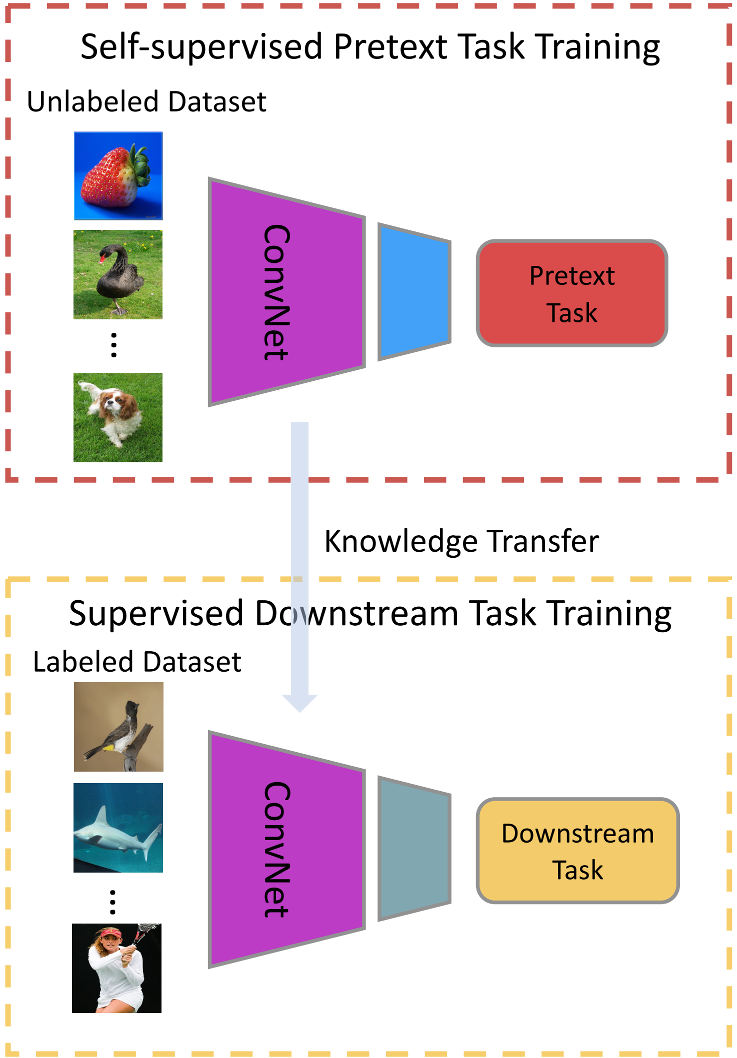
Source: https://www.youtube.com/watch?v=7I0Qt7GALVk

Self-supervised Learning – Definition

Yann LeCun
April 30, 2019 ·

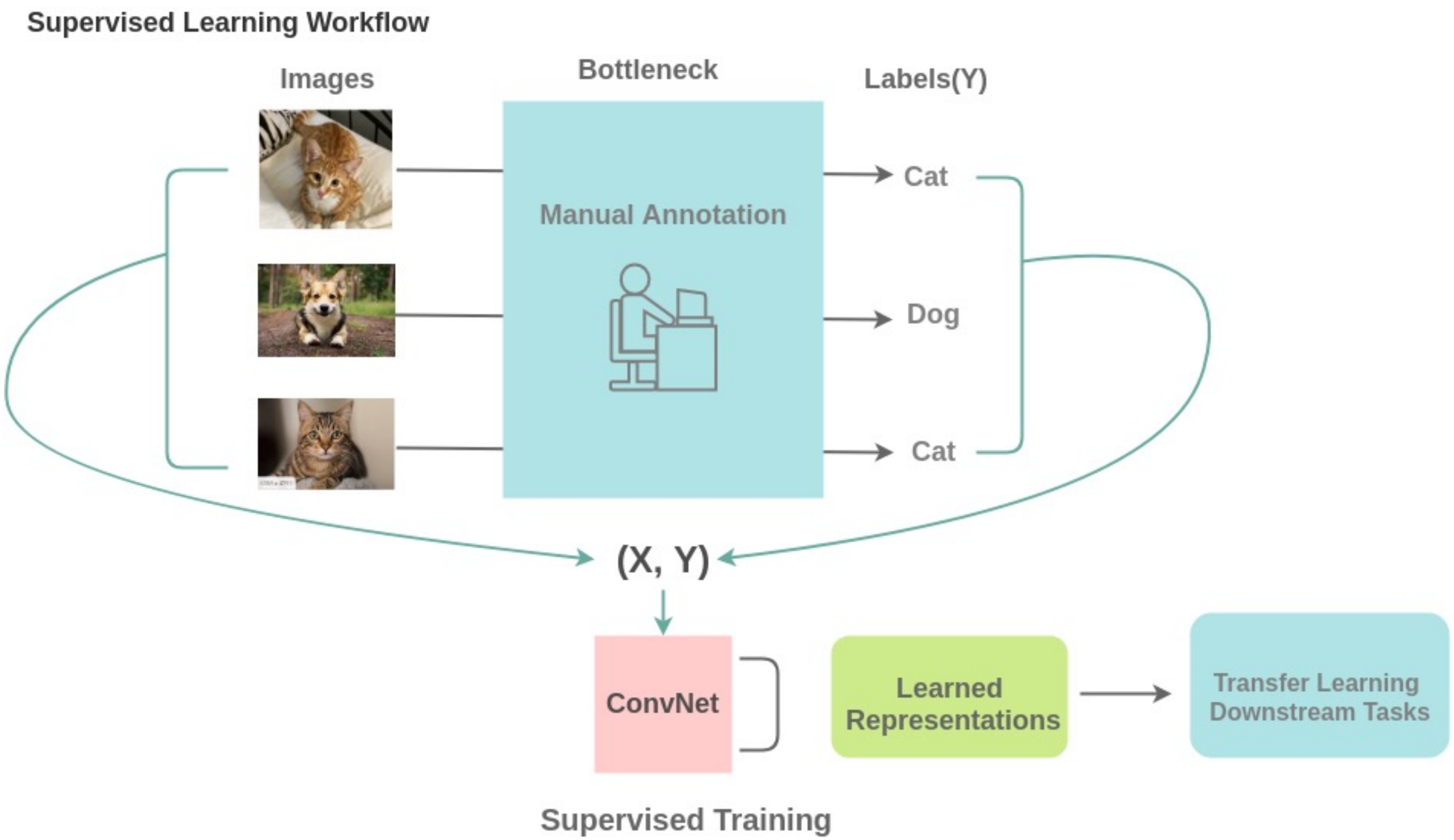
I now call it "self-supervised learning", because "unsupervised" is both a loaded and confusing term.

- Subcategory of unsupervised learning
  - Use pretext/surrogate/pseudo tasks in a supervised fashion, i.e., we have
    - automatically generated labels
    - that can be used as a measure of correctness (for the loss function)
- Downstream task: retrieval, supervised or semi-supervised classification, etc.
- Note: Generative models (e.g., GANs) are also SSL methods



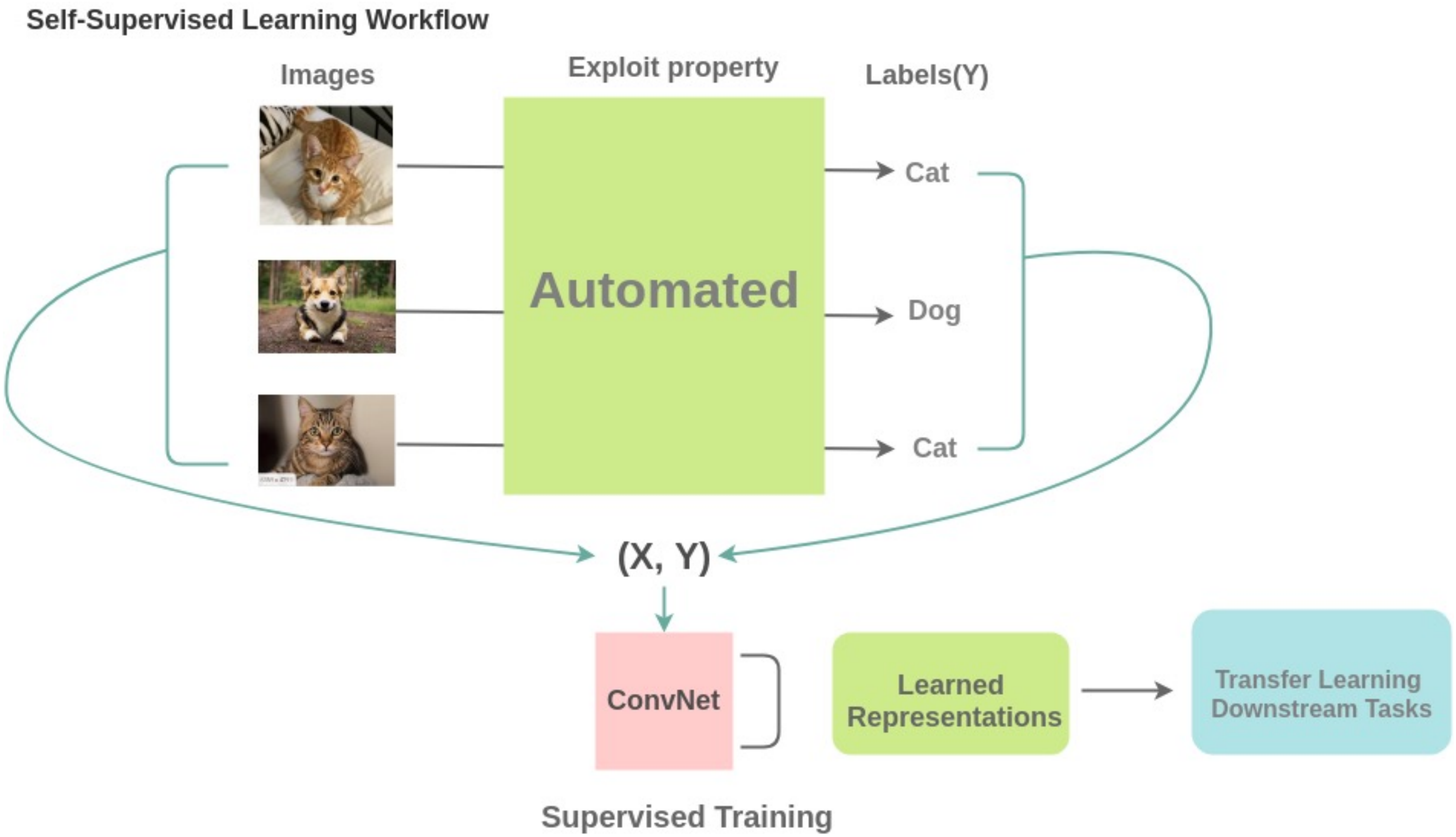
Source: https://www.facebook.com/722677142/posts/10155934004262143/

Advantages of Self-supervised Learning



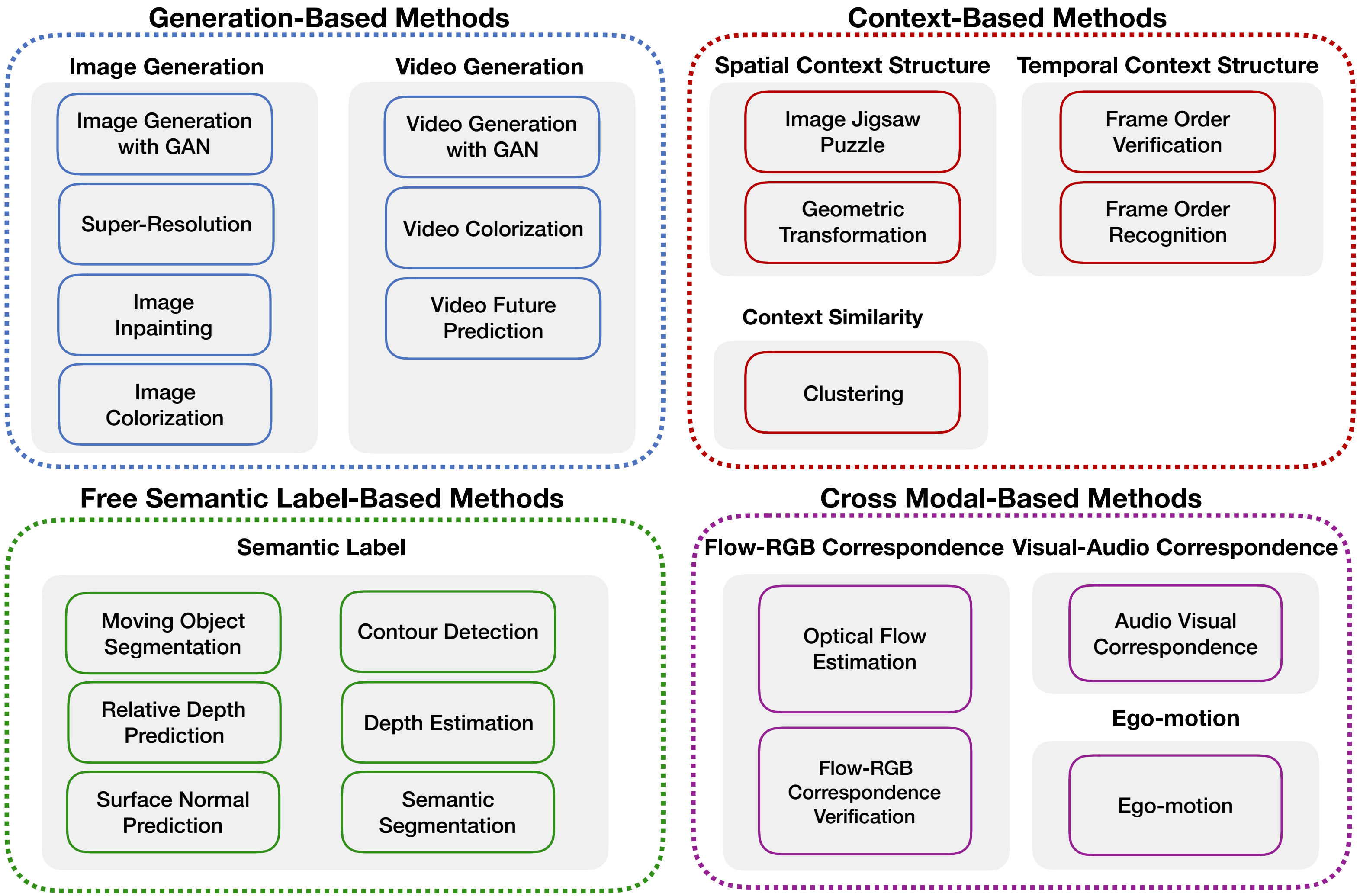
Source: https://amitness.com/2020/02/illustrated-self-supervised-learning/

Advantages of Self-supervised Learning



Source: https://amitness.com/2020/02/illustrated-self-supervised-learning/

Pretext Tasks Overview

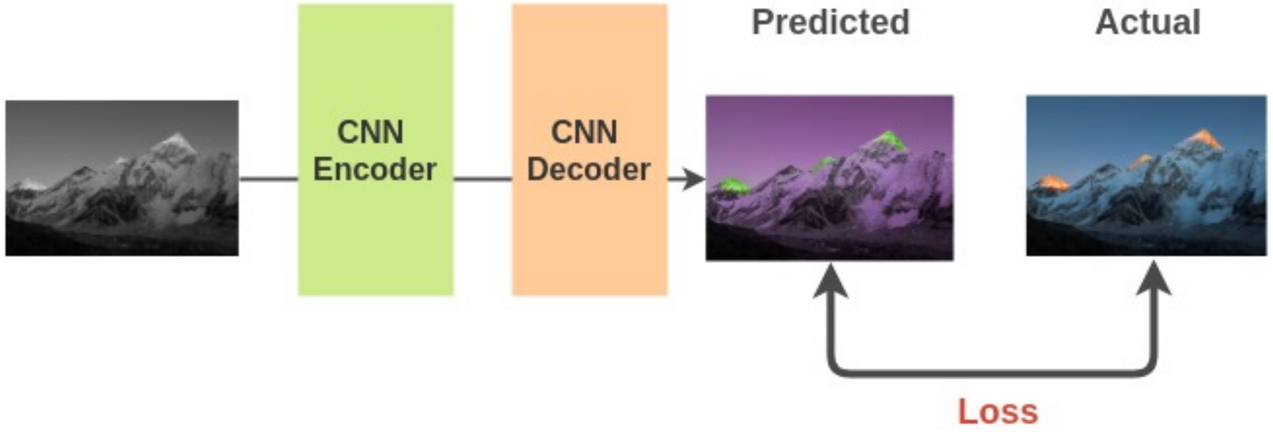


Source: [Jin19]

Image Colorization

Data generation

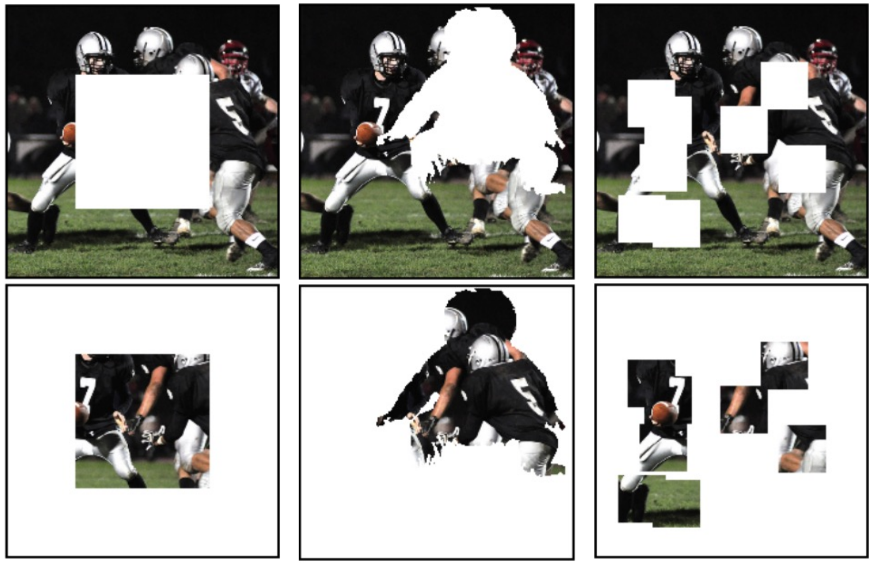
Pretext task: l_2 loss between gray and color version



Source: https://amitness.com/2020/02/illustrated-self-supervised-learning/

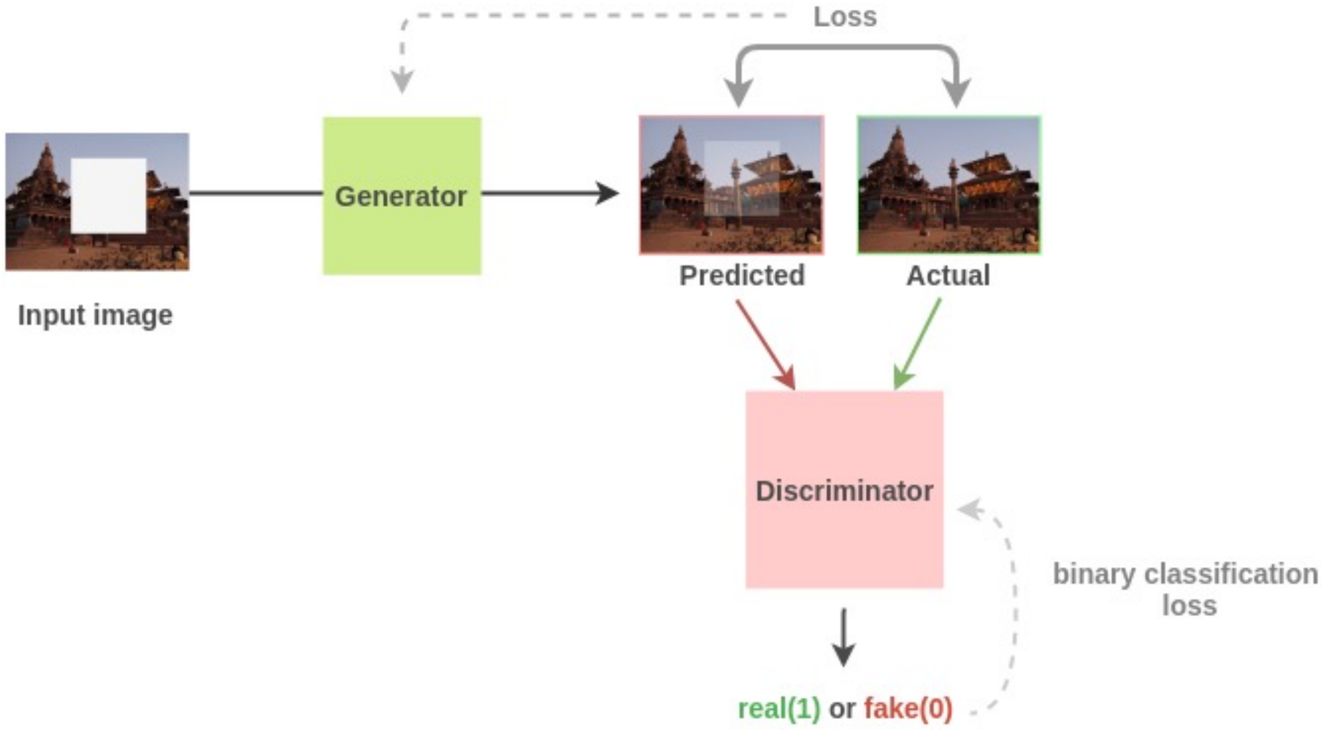
Image Inpainting

Data generation



Source: [Pat16]

Pretext task



Source: https://amitness.com/2020/02/illustrated-self-supervised-learning/

Solve Jigsaw Puzzle

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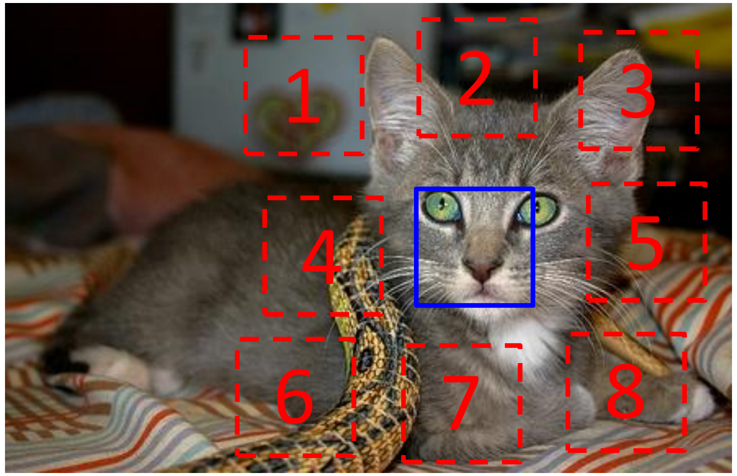
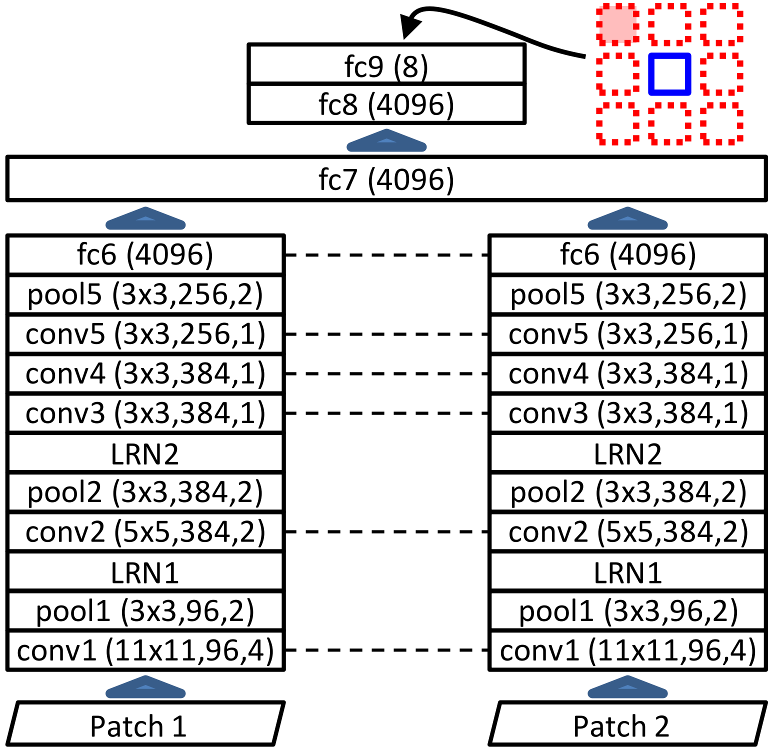
Predict spatial configuration of a patch to selected reference patch (blue)



X = ( , ); Y = 3



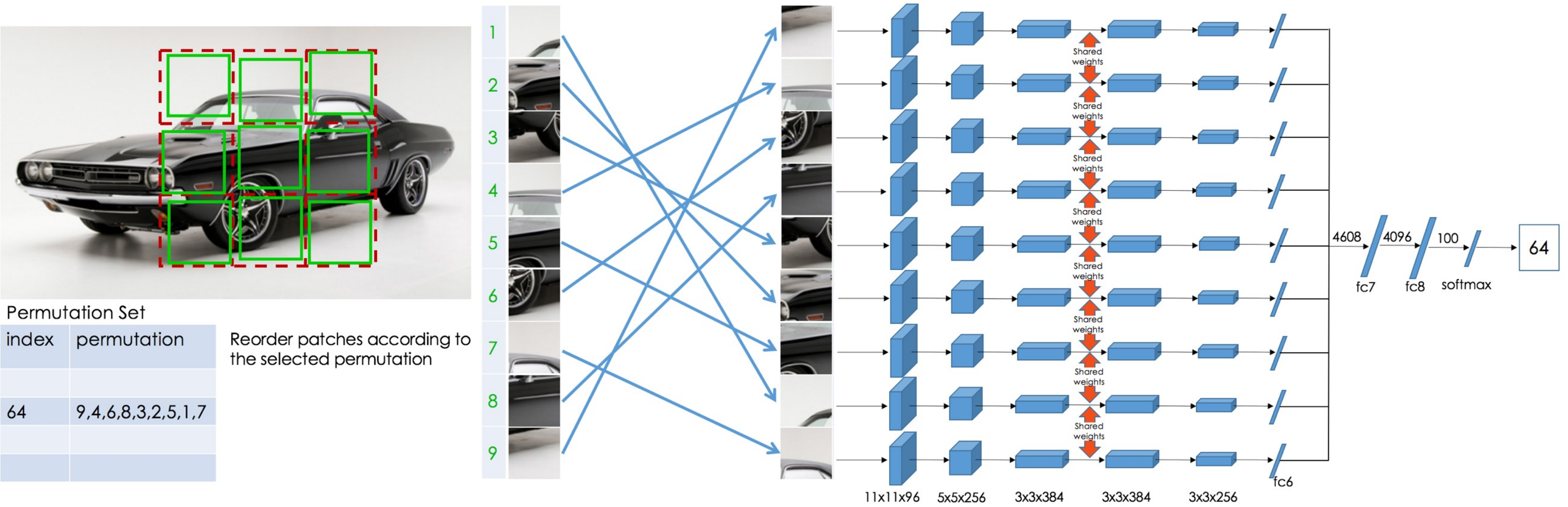
Attention: Avoid trivial shortcuts that the network might learn to use

- boundary patterns, continuing textures $\longrightarrow$ use large enough gaps
- prevent network from only learning about color information: introduce chromatic aberration
  - pre-process images by shifting green and magenta toward gray or
  - randomly drop 2 color channels

Source: [Doe15]

Solve Jigsaw Puzzle++

Predict position of each of the tiles



9 tiles ⟶ 9! = 362 880 possible permutations

After training of Jigsaw problem: Transfer Learning

- Transfer weights of conv layers to AlexNet
- init fully connected AlexNet layers randomly
- use Fast R-CNN architecture for detection

Source: [Nor16]

Solve Jigsaw Puzzle++

Number of permutations	Average hamming distance	Minimum hamming distance	Jigsaw task accuracy	Detection performance
1000	8.00	2	71	**53.2**
1000	6.35	2	62	51.3
1000	3.99	2	54	50.2
100	8.08	2	88	52.6
95	8.08	3	90	52.4
85	8.07	4	91	52.7
71	8.07	5	92	52.8
35	8.13	6	94	52.6
10	8.57	7	97	49.2
7	8.95	8	98	49.6
6	9	9	99	49.7

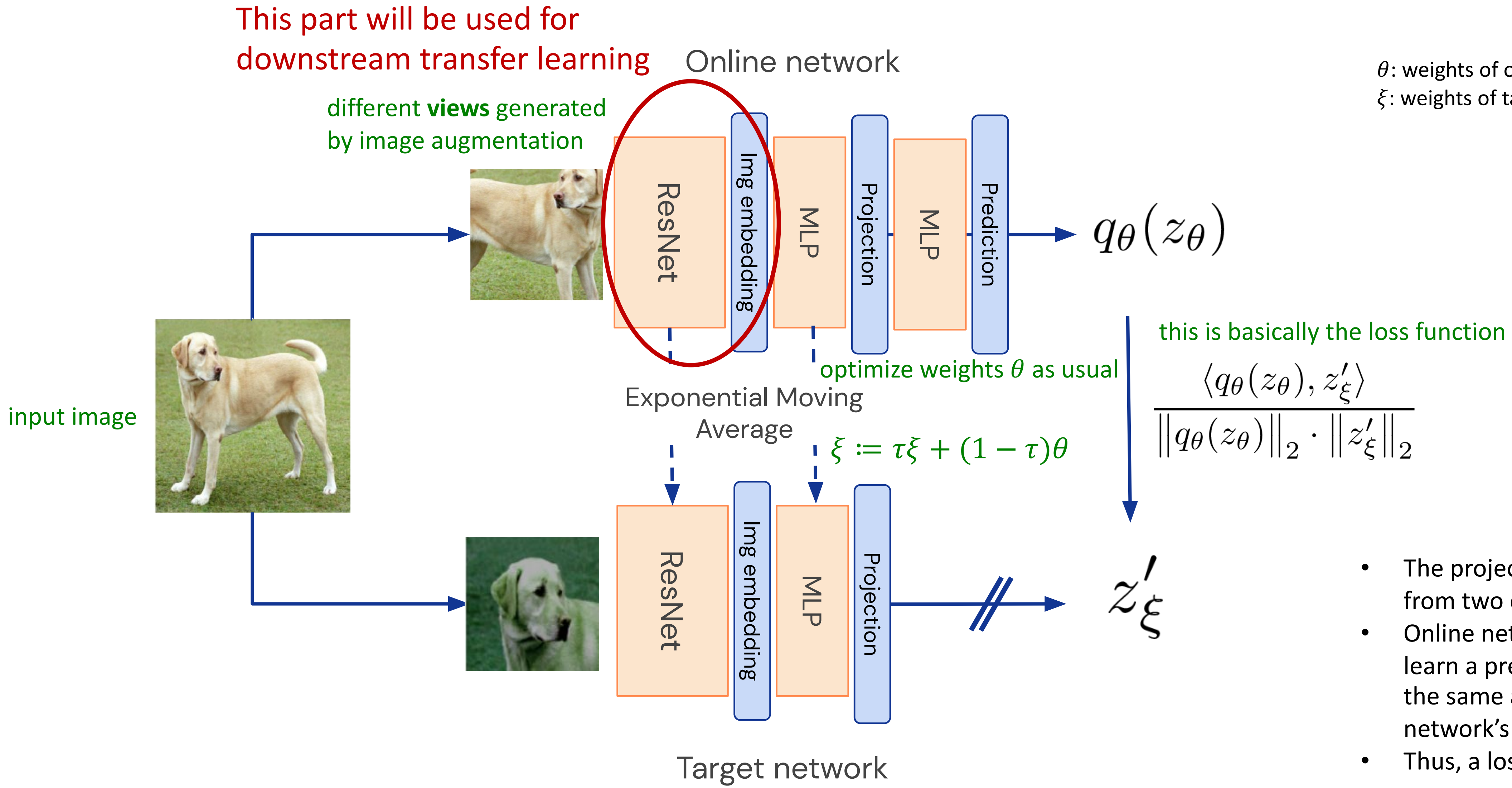
Detection performance: Evaluated after transfer learning on Pascal VOC dataset

Source: [Nor16]

BYOL – Bootstrap Your Own Latent

- New approach to self-supervised learning [Gri20]
- Uses two neural networks that learn from each other
- Transfer weights of one network to downstream tasks
  - 74.3% top-1 classification accuracy on ImageNet (ResNet-50), 91.6% top-5
  - 79.6% top-1 classification accuracy on ImageNet (ResNet-200), 94.8% top-5

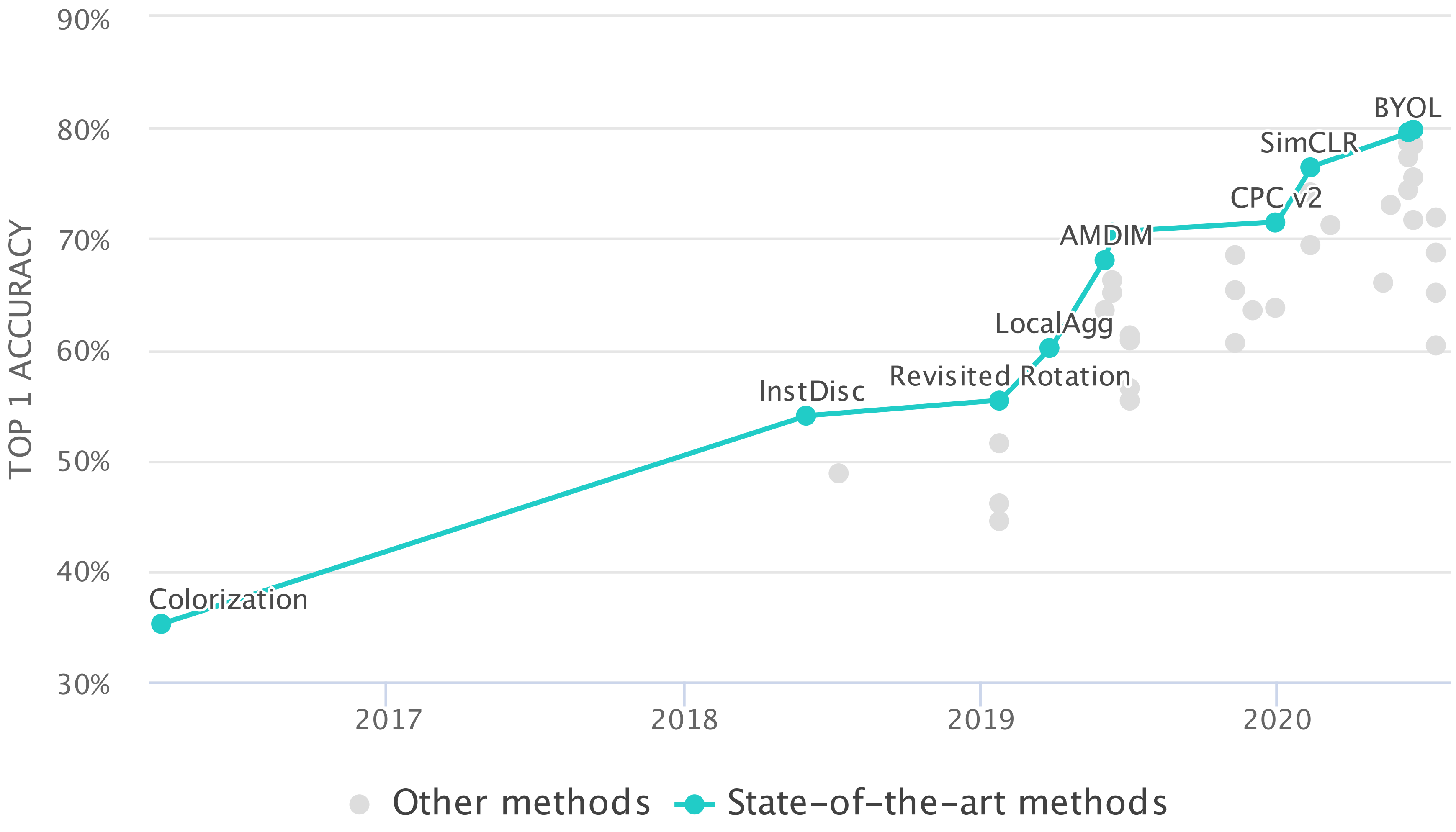
BYOL – Architecture



θ: weights of online network
ξ: weights of target network

- The projections originate from two different views
- Online network tries to learn a prediction that is the same as the target network's projection.
- Thus, a loss can be defined.

SSL – Classification Performance on ImageNet



Source: https://paperswithcode.com/sota/self-supervised-image-classification-on

References

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