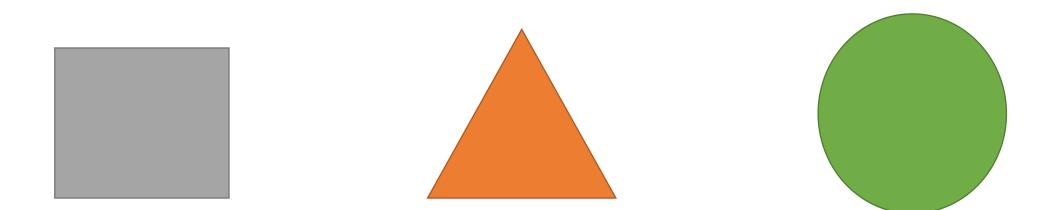
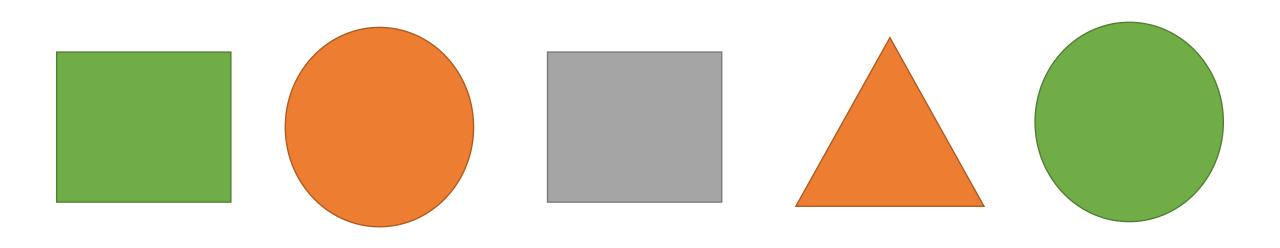
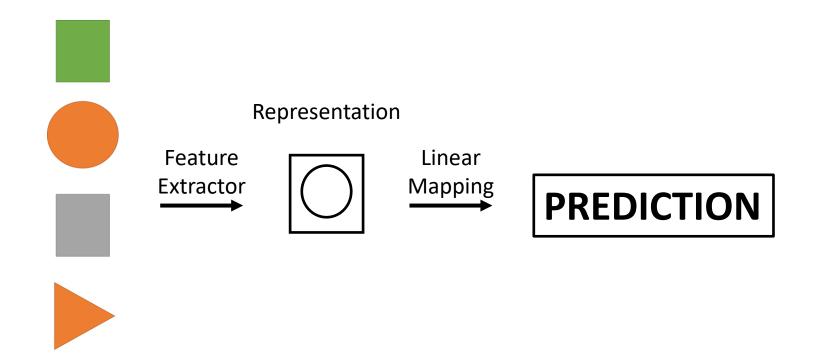


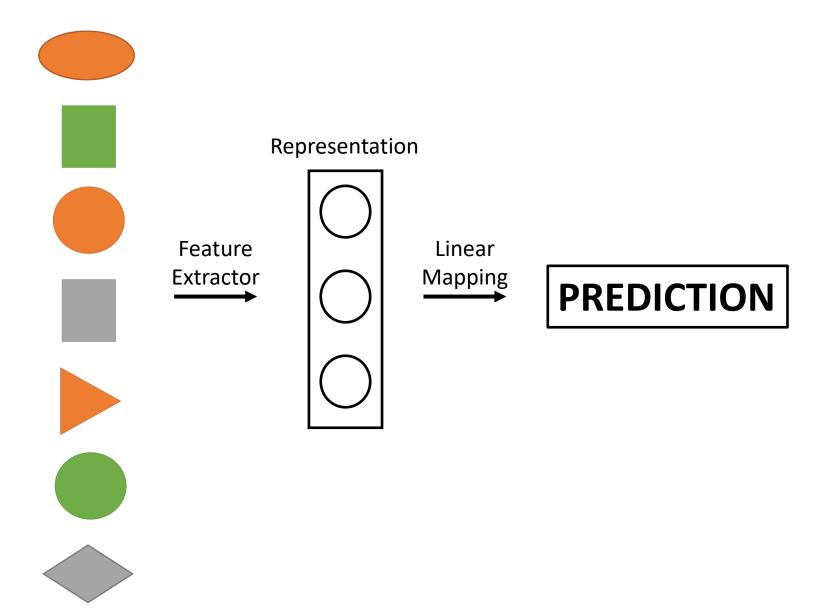


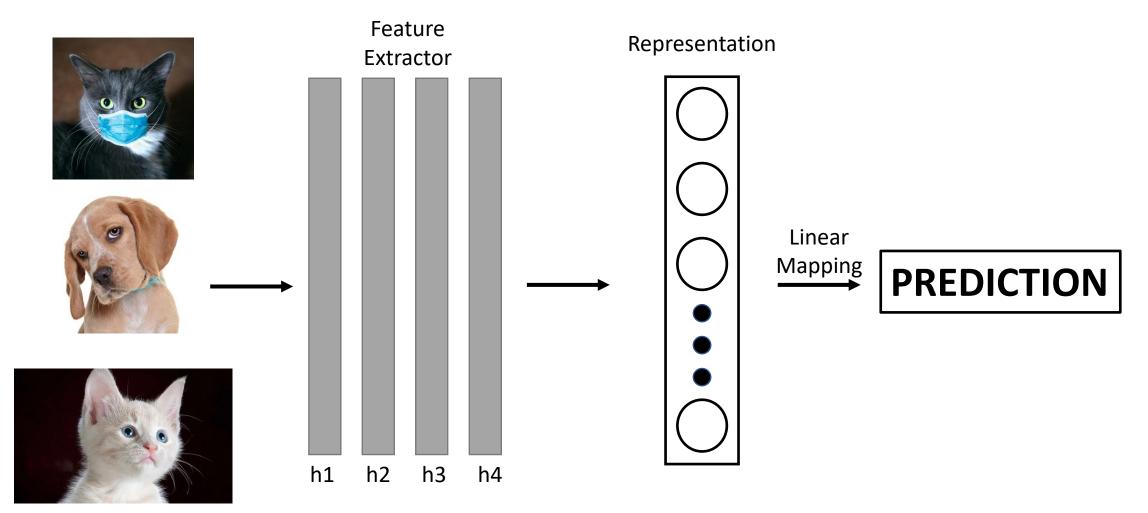
Learning useful representations of inputs, without labels by Ramy Mounir



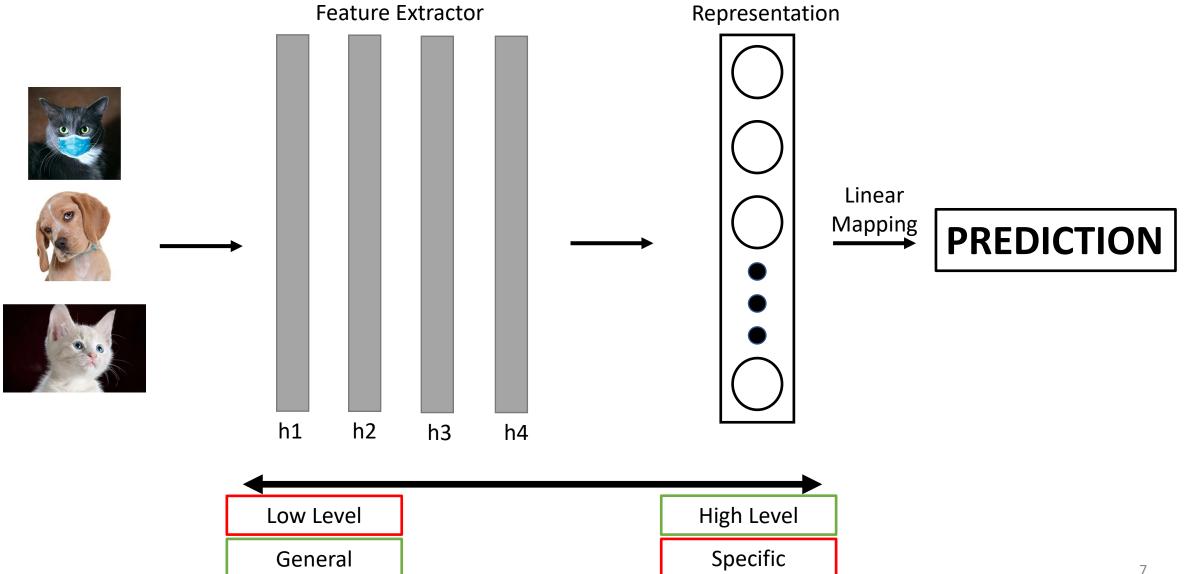




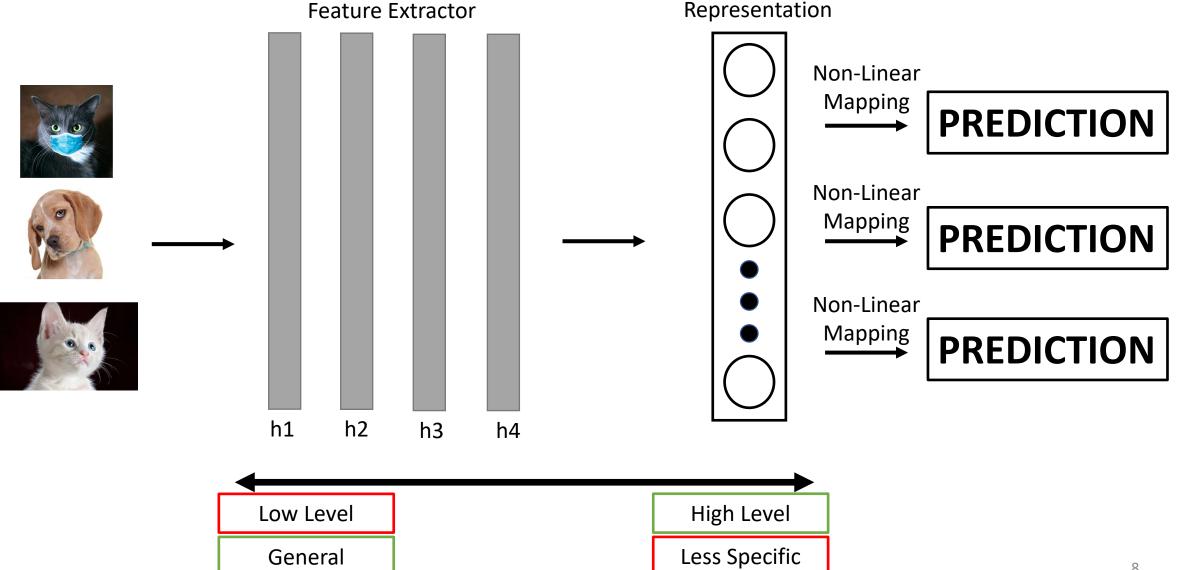




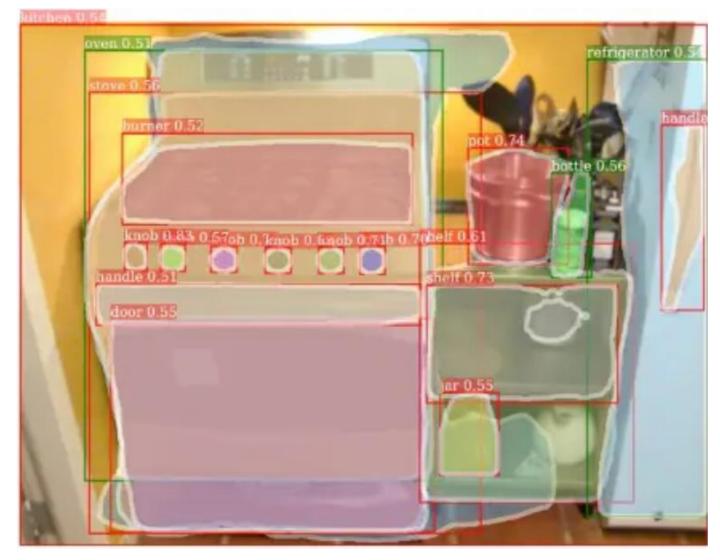
How to extract good features?



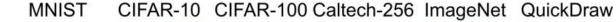
How to extract better features?



• Labels are expensive.



- Labels are expensive.
- Labels are inaccurate



given: 5

corrected: 3

(N/A)

given: 6

alt: 1

correctable

multi-label

neither

non-agreement







(N/A)











given: white stork





given: hat also: flying saucer





alt: elephant

given: pineapple





given: polar bear

alt: raccoon







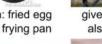


given: fried egg also: frying pan

given: porcupine

alt: hot tub













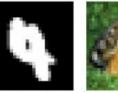


given: hamster

alt: apple

given: rose

given: deer alt: bird



given: 4 alt: 9



given: deer







alt: frog





given: spider alt: cockroach

given: minotaur

alt: coin alt: flatworm

given: eel



10



given: ewer corrected: teapot corrected: black stork







- Labels are expensive.
- Labels are inaccurate

NO LABEL			LABELED "IPOD"			LABELED "LIBRARY"			LABELED "PIZZA"		
	Granny Smith	85.61%		Granny Smith	0.13%		Granny Smith	1.14%		Granny Smith	0.89%
	iPod	0.42%		iPod	99.68%		iPod	0.08%		iPod	0%
1 × × ×	library	0%	DIE	library	0%	IDD ADY			Dina 15	library	0%
	pizza	0%	iPod F	pizza	0%	ORAK	pizza	0%	PIZZI	pizza	65.35%
	rifle	0%	A MARTIN	rifle	0%	1	rifle	0%	1	rifle	0%
1.1.1.1	toaster	0%		toaster	0%	S The s	toaster	0%	1.5 1	toaster	0%
SER SERVICE	laptop computer	15.98%	STATE AND A STATE	laptop computer	4.03%	NOT THE REAL PROPERTY OF	laptop computer	37.6%	CONTRACTOR AND	laptop computer	18.89%
	iPod	0%				100121	iPod	0%	10(77)	iPod	0%
	library	0%	A MARKED	library	0%	A PARTY A	library	5.24%	A PARTY	library	0%
americal	pizza	0%		pizza	0%	and the second s	pizza	0%		pizza	59.3%
Ber	rifle	0%	Barran	rifle	0%	- Barris	rifle	0%	Baller	rifle	0%
	toaster	0%		toaster	0%		toaster	0%		toaster	0%
Company and	coffee mug	61.71%		coffee mug	2.97%		coffee mug	2.13%		coffee mug	55.42%
	iPod	0%	ES DA TO	iPod	95.43%	The Tan	iPod	0%	C PATE	iPod	0%
	library	0%	L'an	library	0%	I DARY MA	library	80.77%	190	library	0%
	pizza	0%	iPod	pizza	0%	LIBK'	pizza	0%	PIZ	pizza	26.39%
and the second	rifle	0%		rifle	0%		rifle	0%		rifle	0%
	toaster	0%		toaster	0%		toaster	0%		toaster	0.04%
	rotary dial telephone	98.33%		rotary dial telephone	47.93%		rotary dial telephone	80.94%		rotary dial telephone	81.12%
A COLOR	iPod	0%	NEW HOLEN	iPod	25.65%	UBRAR)	iPod	0%		iPod	0%
	library	0%		library	0%		library	9.68%		library	0%
	pizza	0%		pizza	0%		pizza	0%		pizza	3.48%
	rifle	0%		rifle	0%		rifle	0%		rifle	0%
///	toaster	0%		toaster	0.04%		toaster	0%		toaster	0.03%
	plant pot	50.58%	1	plant pot	4.99%		plant pot	19%		plant pot	12.63%
The second	iPod	0%	The Chine		93.5%		iPod	0%	The Designer	iPod	0%
H- CAR	library	0%	A CAR	library	0%	A CONSTRUCTION	library	42.07%	A A A A	library	0%
1031	pizza	0%	DID I	pizza	0%	IRDAP	pizza	0%		pizza	50.17%
	rifle	0%	Pod	rifle	0%	OKA	rifle	0%		rifle	0%
Port and a state	toaster	0%	CHERRY CONTRACT	toaster	0%	Contraction of the second	toaster	0%	Card Martin	toaster	0%

- Labels are expensive.
- Labels are inaccurate
- Labels encourage tailored and task-dependent features
 - e.g., Using human detector for tracking

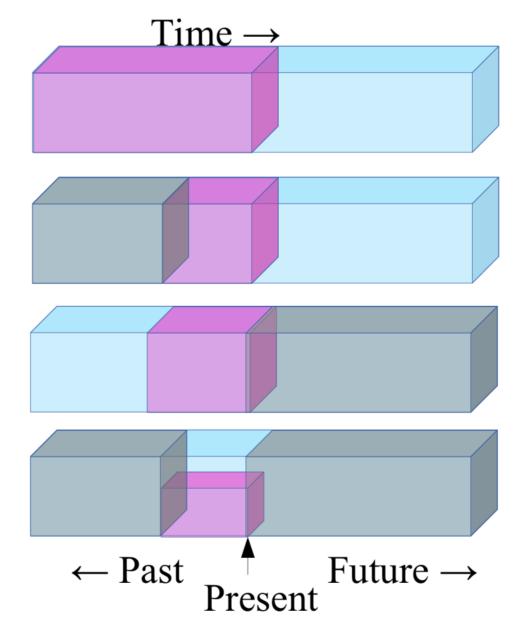
• Past predicts the future

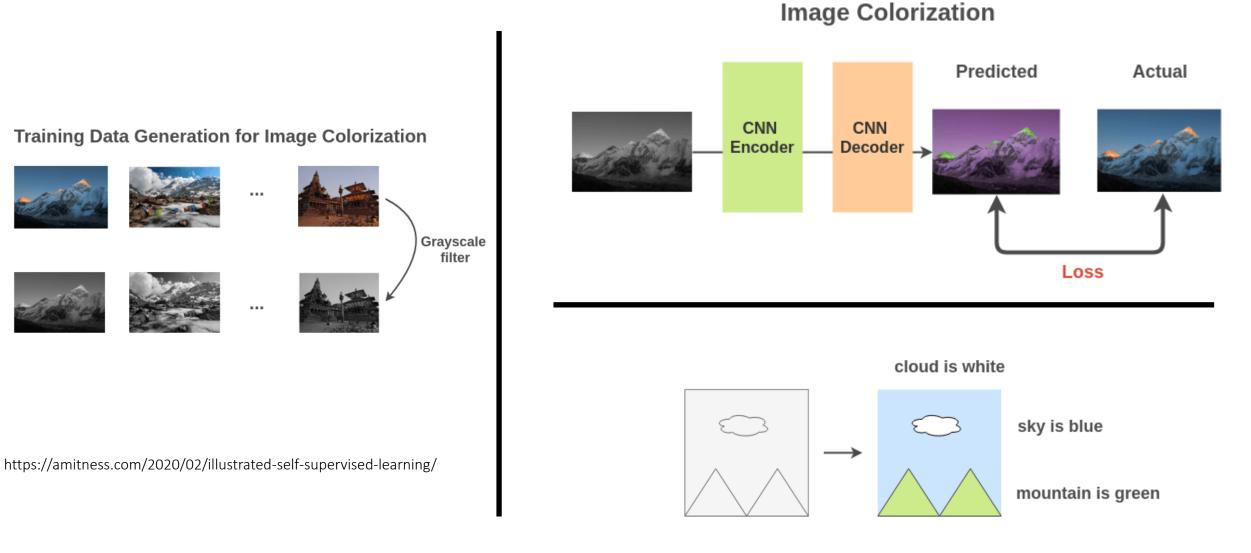
• Recent past predicts future

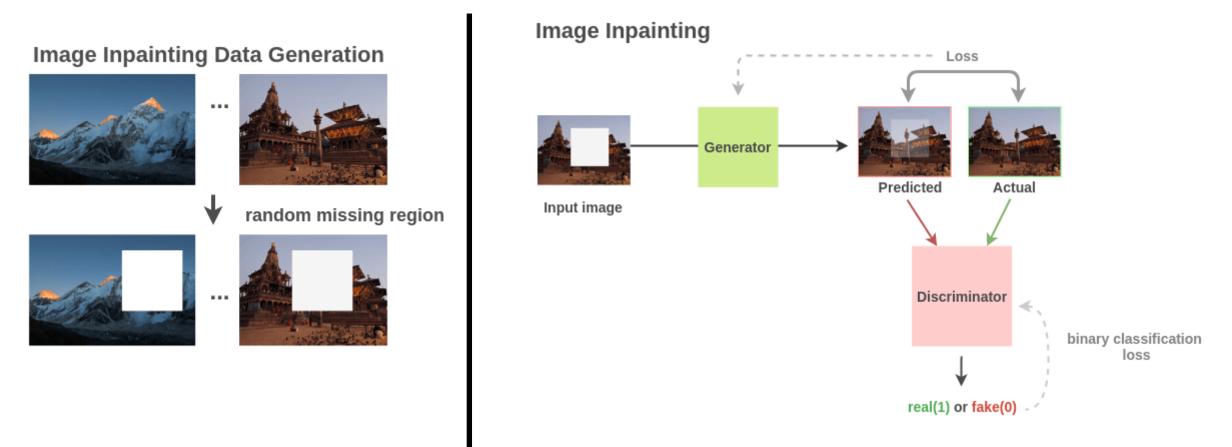
• Present predicts the past

• Visible predicts occluded

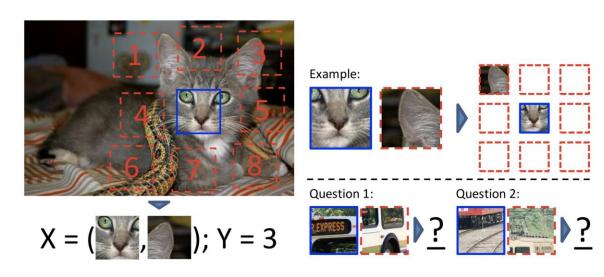
Adopted from Yann Lecun Presentation on self-supervised learning



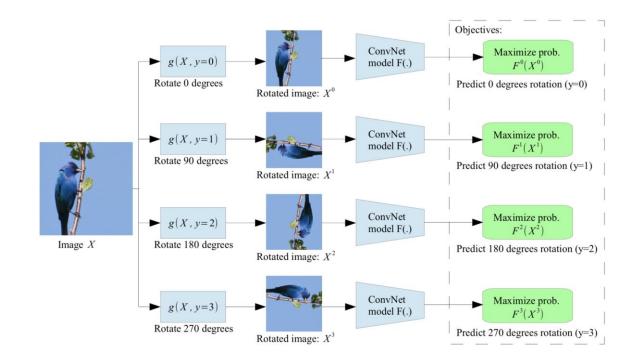




https://amitness.com/2020/02/illustrated-self-supervised-learning/



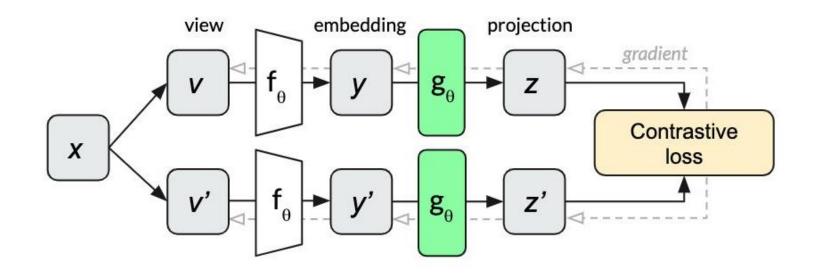
Doersch, Carl, Abhinav Gupta, and Alexei A. Efros. "Unsupervised visual representation learning by context prediction." Proceedings of the IEEE international conference on computer vision. 2015.

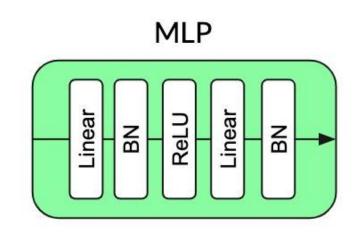


Gidaris, Spyros, Praveer Singh, and Nikos Komodakis. "Unsupervised representation learning by predicting image rotations." arXiv preprint arXiv:1803.07728 (2018).

Contrastive approaches

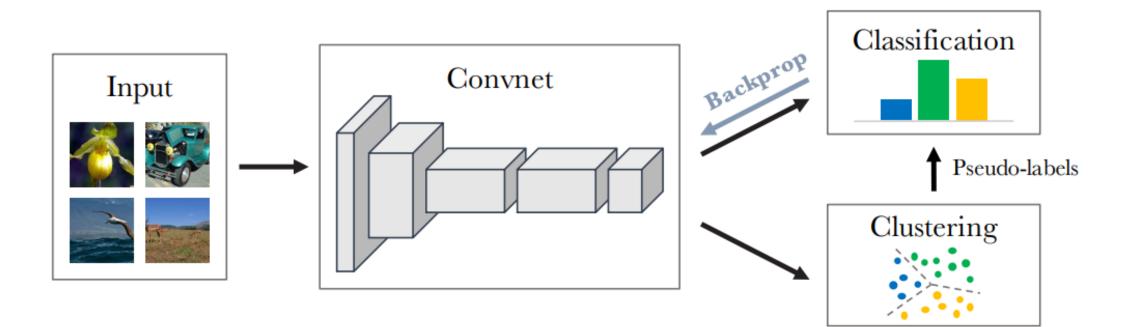
Contrastive approaches - SimCLR



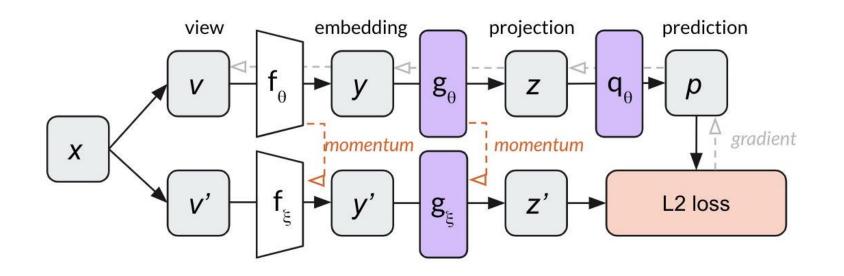


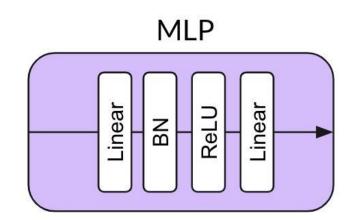
Chen et al. ICML 2020 [Image Source]

Clustering approaches

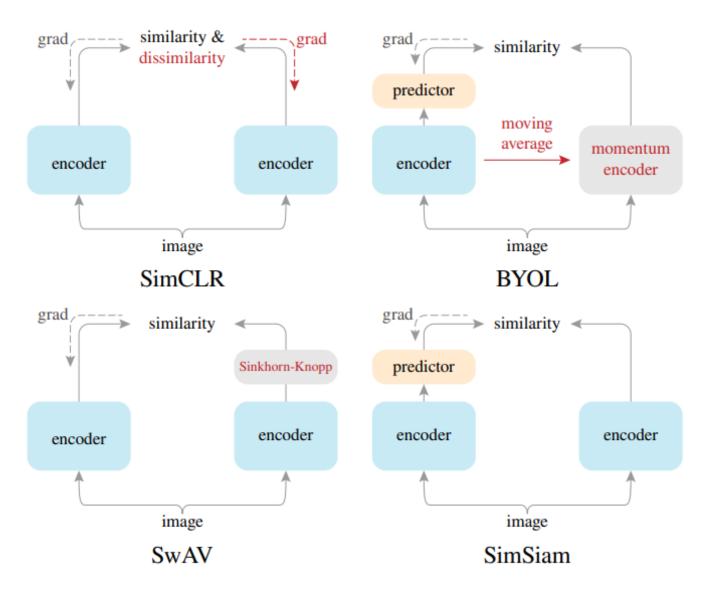


Momentum Encoder - BYOL



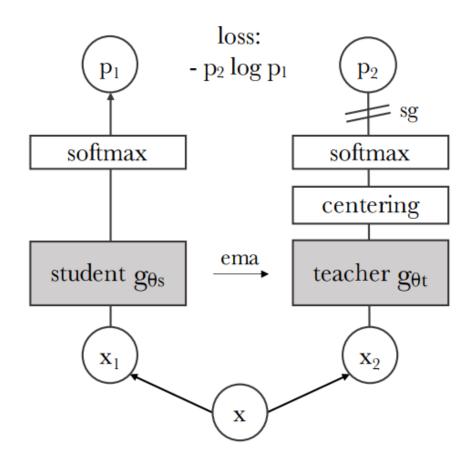


Simple Siamese - SimSiam



Chen et al. 2020

Momentum Encoder - DINO

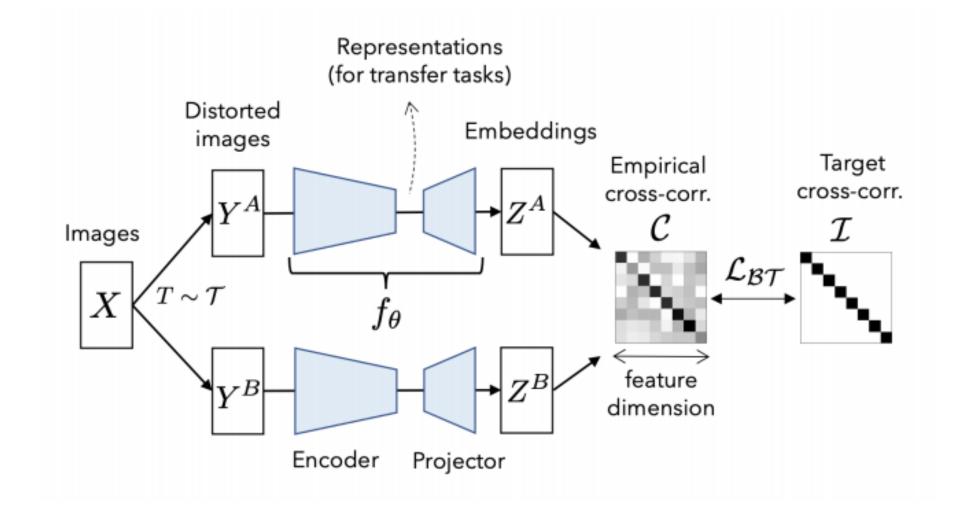






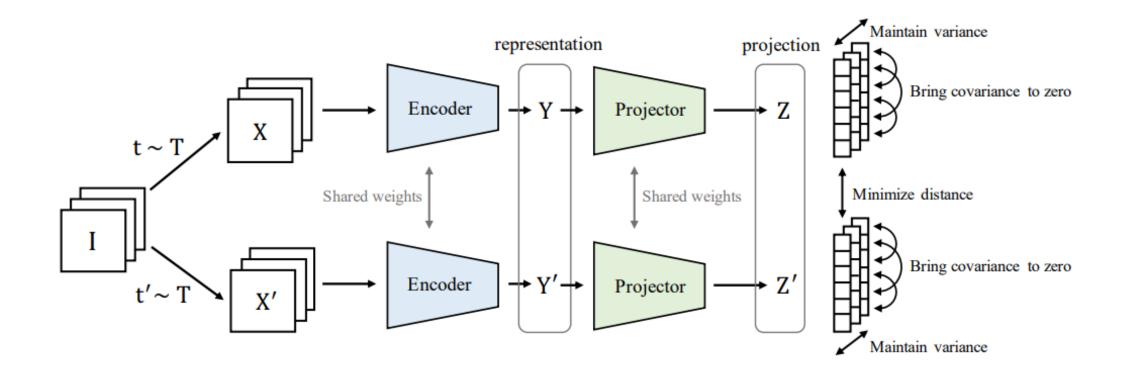
Caron et al. ICCV 2021

Symmetrical – Barlow Twins



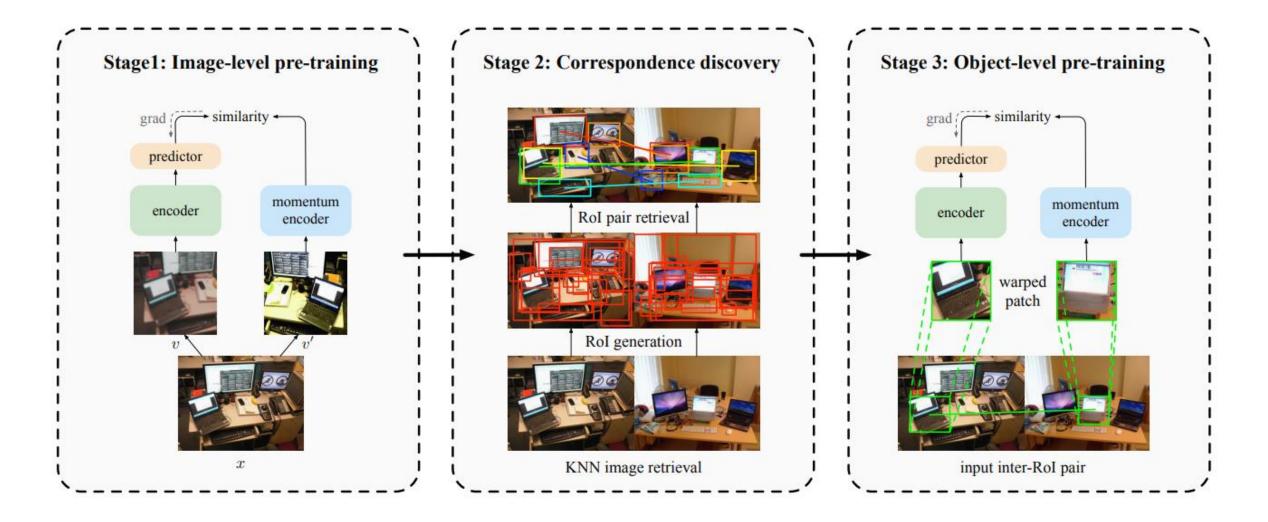
Zbontar et al. 2021

Symmetrical – VICReg



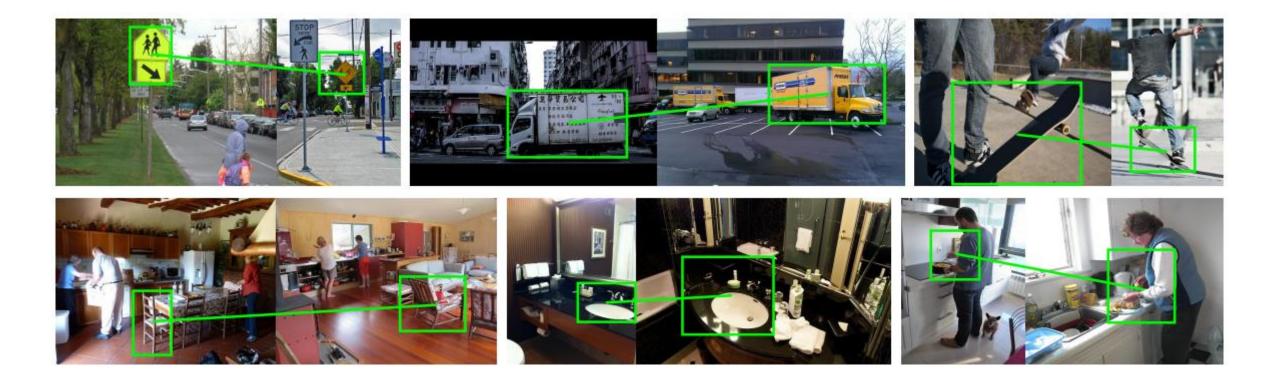
Bardes et al. 2021

Object Level - ORL



Xie et al. 2021

Object Level - ORL



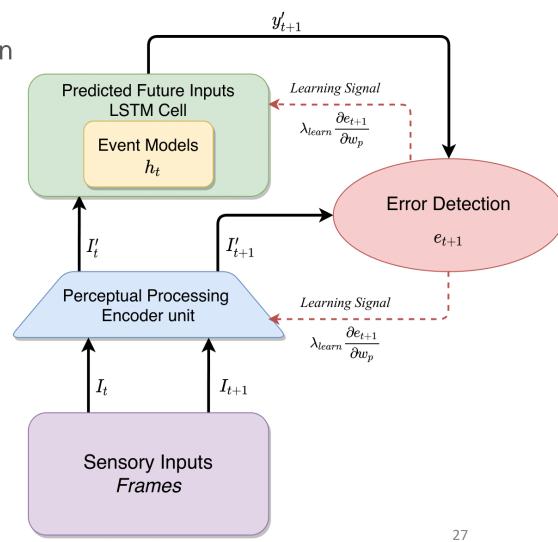
Self Supervised Event Segmentation

- LSTM cell for internal memory of event model.
- Error detection implemented as a low pass filter on prediction error running average.
- Gating signal triggered when error is above 1.5 times the running average.
- Adaptive learning controls learning rate

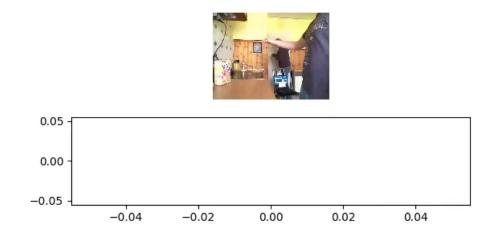
$$P_q(t) = P_q(t-1) + \frac{1}{n}(E_P(t) - P_q(t-1))$$

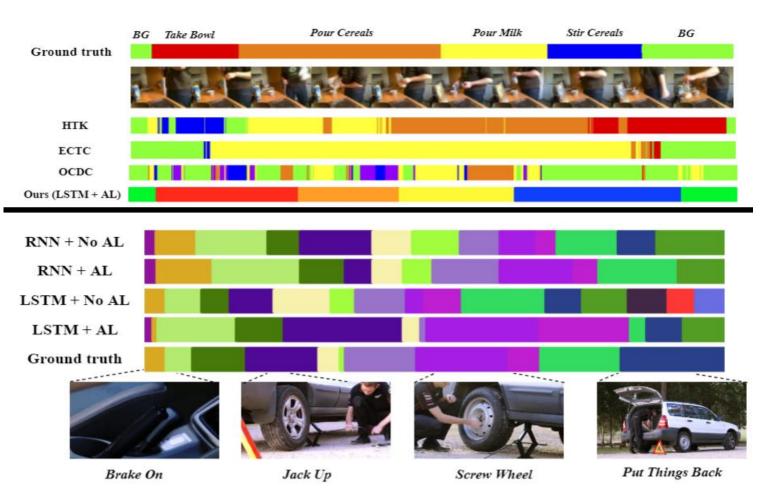
$$G(t) = \begin{cases} 1, & \frac{E_P(t)}{P_q(t-1)} > \psi_e \\ 0, & \text{otherwise} \end{cases}$$

Aakur, S. N., & Sarkar, S. (2019). A perceptual prediction framework for self supervised event segmentation. In *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition* (pp. 1197-1206).



Self Supervised Event Segmentation

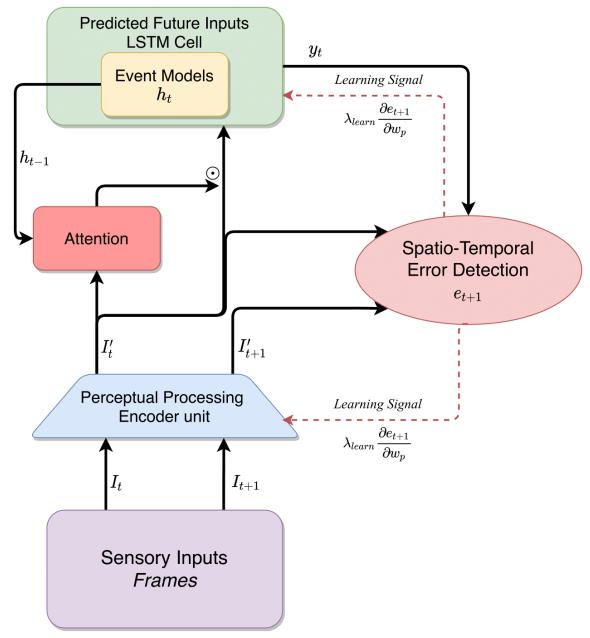




Wildlife Extended Videos

- Bahdanau attention is used to visualize the location of the bird.
- Motion-weighted loss is used instead of pure prediction loss.

$$e_t = ||(I'_{t+1} - y'_t)^{\odot 2} \odot (I'_{t+1} - I'_t)^{\odot 2}||^2$$



Mounir, R., Gula, R., Theuerkauf, J., & Sarkar, S. (2020). Temporal Event Segmentation using Attention-based Perceptual Prediction Model for Continual Learning. *arXiv preprint arXiv:2005.02463*.

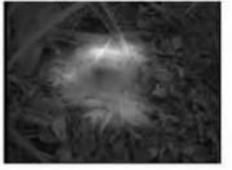
Wildlife Extended Videos



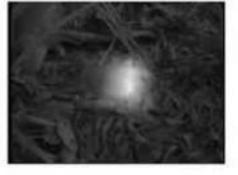
Raw Video Frames



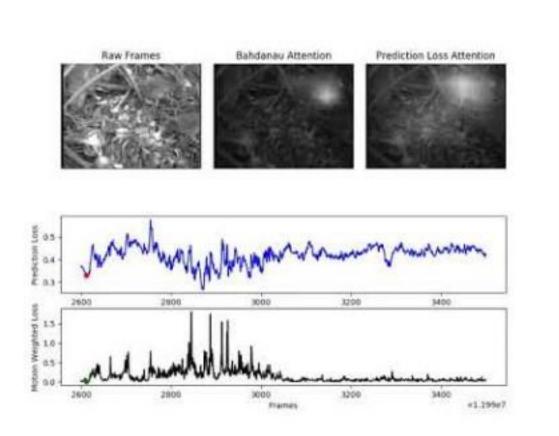
Bahdanau Attention

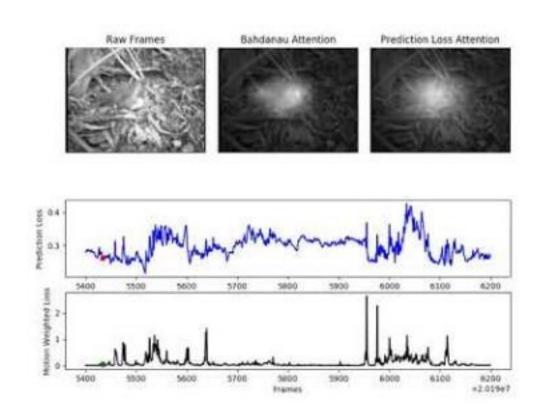


Bahdanau Attention



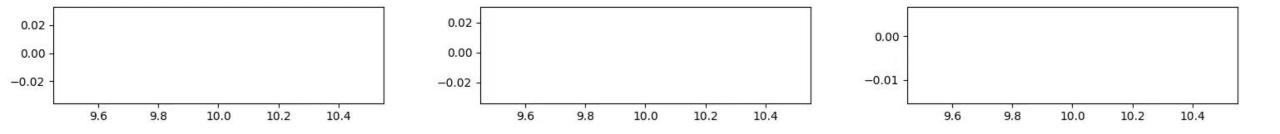
Wildlife Extended Videos





Other Domains





Thank you Questions?





