

Learning Methods

Dual, Self-supervised, Self-augmented Learnings

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2019, Peking University





- Dual, Self-supervised, Self-augmented Learnings
- Dual Learning
- Self-supervised Learning
- Self-augmented Learning
- Summary

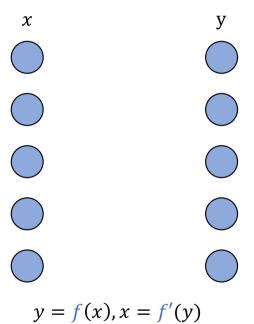


From Mapping Point of View Dual, Self-supervised, Self-augmented Learning



From Mapping Point of View

Data in both input and output (Learn the mapping f, f')

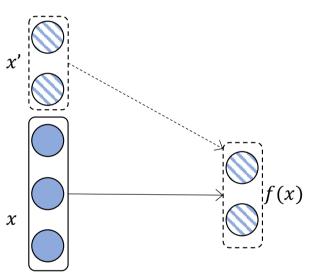


$$y = f(x), x = f'(y)$$

(Unsupervised) Dual Learning

- VAE
- CycleGAN

Data in input x, x' only with known mapping f'(Learn the mapping *f*)

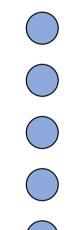


$$x' = f(x)$$

Self-supervised Learning

- Word2Vec
- **Denoising Autoencoder**

Data in input only with known inverse mapping f'(Learn the mapping *f* and output *y*)



$$y = f(x), x = f'(y)$$

Self-augmented Learning



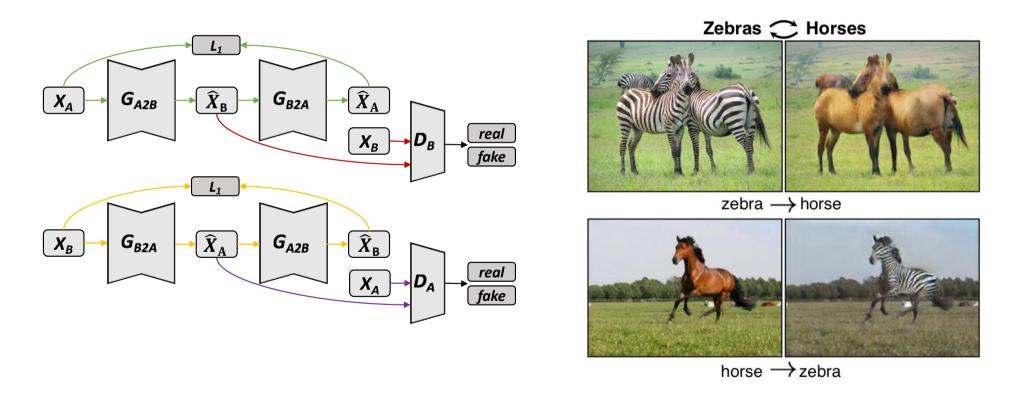


- Motivation
 - Human label is expensive
 - No feedback if using unlabeled data

Application	Primal Task	Dual (Inverse) Task
Machine translation	Translate language from A to B	Translate language from B to A
Speed processing	Speech to text (STT)	Text to speech (TTS)
Image understanding	Image captioning	Image generation
Conversation engine	Question	Answer
Search engine	Search	Query

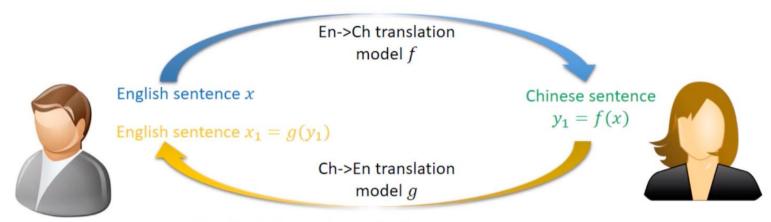


Example: Unpaired Image-to-Image Translation





Example: Language Translation



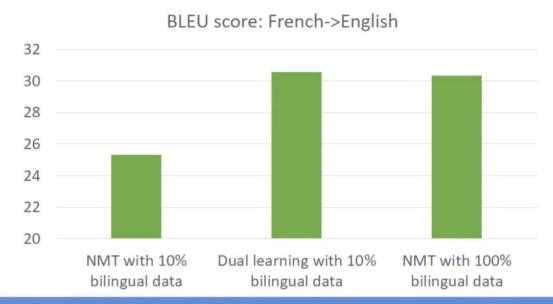
Feedback signals during the loop:

- $s(x, x_1)$: BLEU score of x_1 given x
- L(y) and $L(x_1)$: Likelihood and language model of y_1 and x_1

Reinforcement learning is used to improve the translation models from these feedback signals



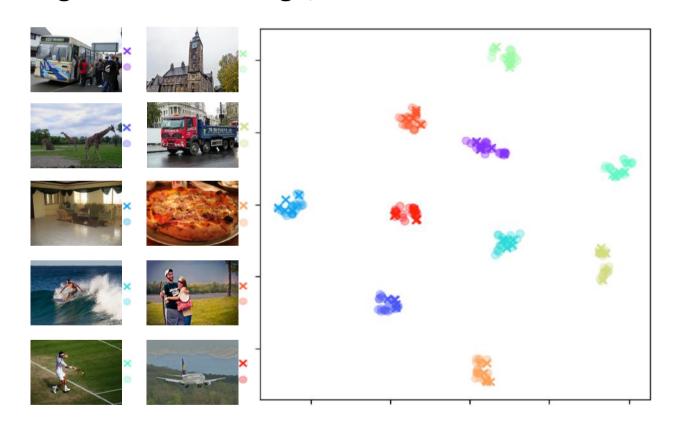
Example: Machine Translation



Starting from initial models obtained from only 10% bilingual data, dual learning can achieve similar accuracy as the NMT model learned from 100% bilingual data!



• Example: Image-to-Text-to-Image, I2T2I





Example: Image-to-Text-to-Image, I2T2I





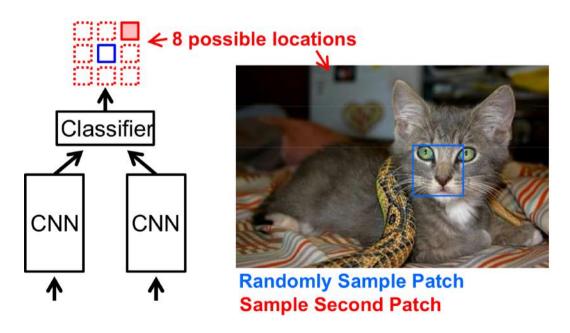


- Self-supervised learning is autonomous supervised learning, it learns to predict part of its input from other parts of its input.
- Examples: Word2Vec, Denoising Autoencoder
- Self-supervised vs. unsupervised learning: Self-supervised learning is like unsupervised Learning because the system learns without using explicitly-provided labels. It is different from unsupervised learning because we are not learning the inherent structure of data. Self-supervised learning, unlike unsupervised learning, is not centered around clustering and grouping, dimensionality reduction, recommendation engines, density estimation, or anomaly detection.



Image Example: Relative Positioning

Train network to predict relative position of two regions in the same image

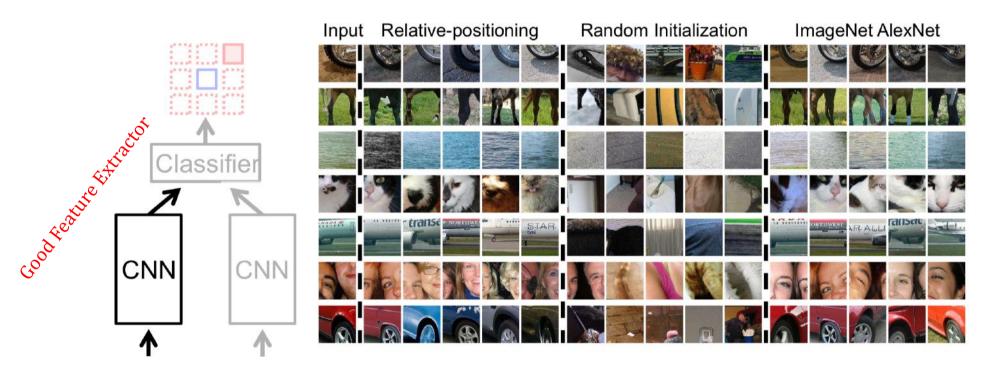


Unsupervised visual representation learning by context prediction, Carl Doersch, Abhinav Gupta, Alexei A. Efros, ICCV 2015



Image Example: Relative Positioning

Learn high-level features



Unsupervised visual representation learning by context prediction, Carl Doersch, Abhinav Gupta, Alexei A. Efros, ICCV 2015



• Image Example: Colourization

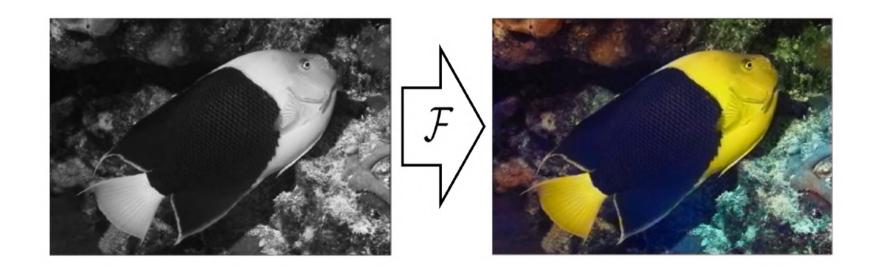




Image Example: 3D pose estimation

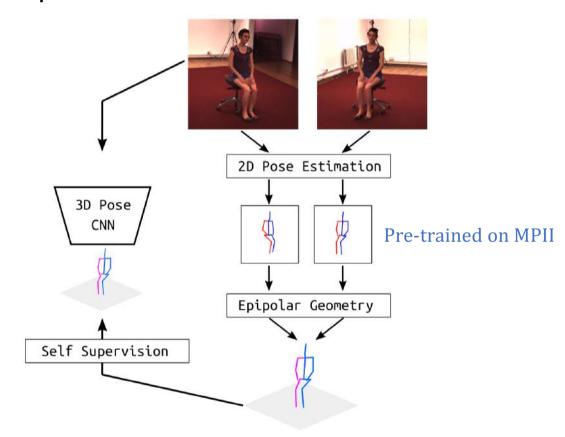




Image Example: Learn from Rotation





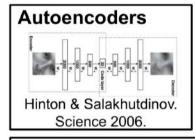


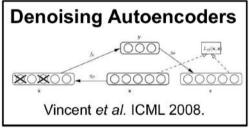


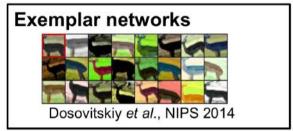
Unsupervised representation learning by predicting image rotations, Spyros Gidaris, Praveer Singh, Nikos Komodakis, ICLR 2018

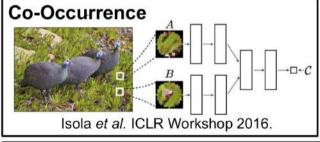


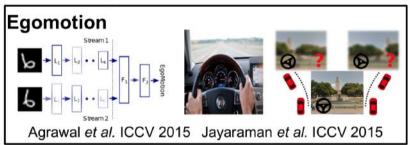
Image Examples

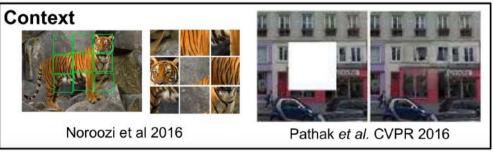


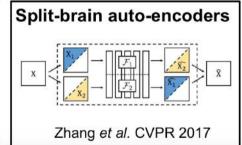














Video Example















- Videos contain
 - Color, Temporal info
- Possible proxy tasks
 - Temporal order of the frames
 - Optical flow: Motion of objects
 - ..



Video Example: Shuffle and Learn

Given a start and an end, can this point lie in between?

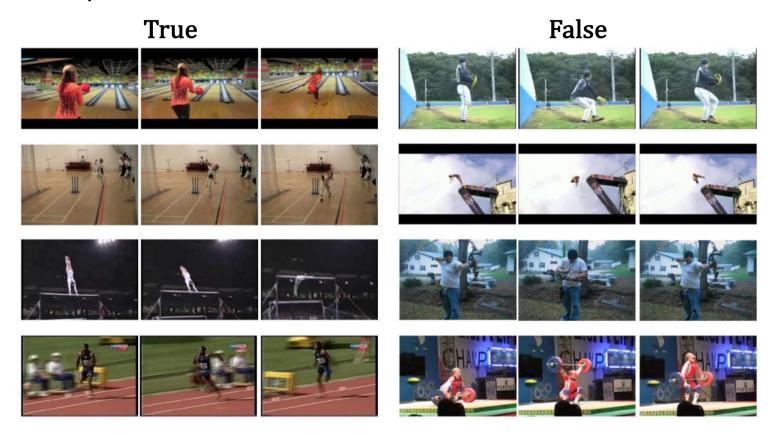








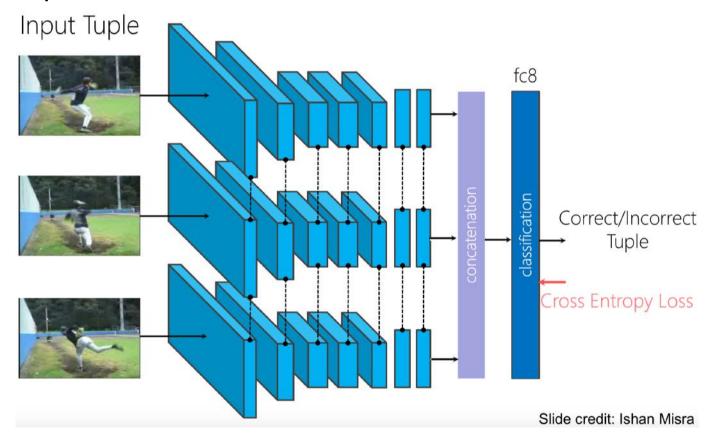
Video Example: Shuffle and Learn



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Self-supervised Learning

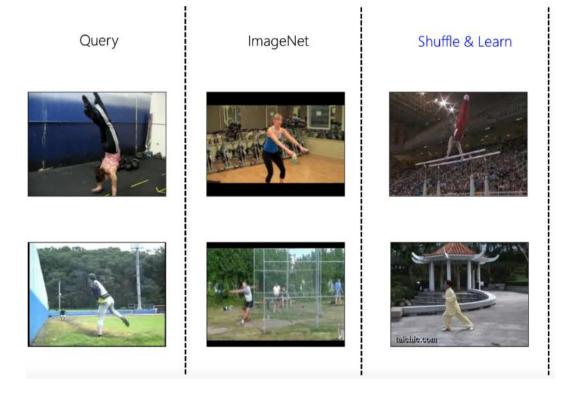
Video Example: Shuffle and Learn





Video Example: Shuffle and Learn

Image Retrieval: Nearest Neighbors of Query Frame (FC5 outputs)





Video Example: Shuffle and Learn

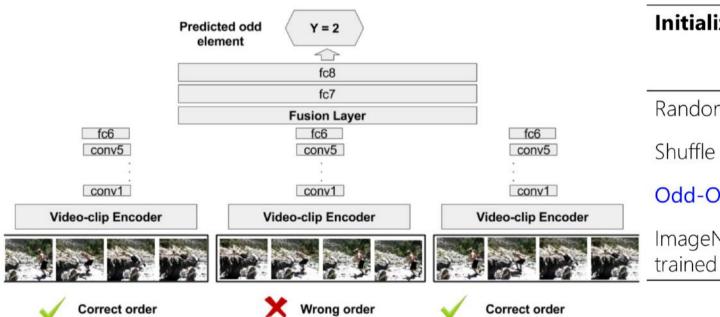




Dataset	Initialization	Mean Classification Accuracy
UCF101	Random	38.6
	Shuffle & Learn	50.2
	ImageNet pre-trained	<u>67.1</u>



Video Example: Odd-One-Out



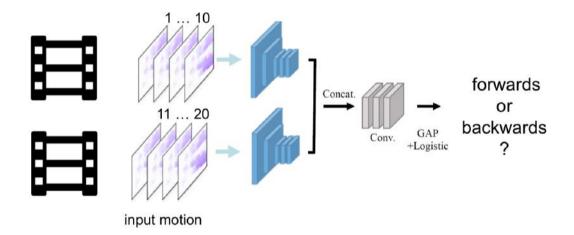
Initialization	Mean Classification Accuracy
Random	38.6
Shuffle and Learn	50.2
Odd-One-Out	60.3
lmageNet pre- trained	<u>67.1</u>



Video Example: Learning the Arrow of Time

Forward or backward plays?





- Depending on the video, solving the task may require
- (a) low-level understanding (e.g. physics)
- (b) high-level reasoning (e.g. semantics)
- (c) familiarity with very subtle effects
- (d) camera conventions

- Input: optical flow in two chunks
- Final layer: global average pooling to allow class activation map (CAM)



• Video Example: Temporal Coherence of Color

Colorize all frames of a grey scale version using a reference frame









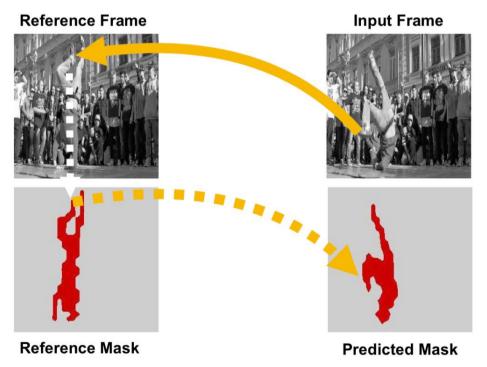
Reference Frame

What color is that?



• Video Example: Temporal Coherence of Color

Tracking Emerges: Only the first frame is given, colors indicate different instances



Tracking Emerges by Colorizing Videos

Vondrick, Shrivastava, Fathi, Guadarrama, Murphy, ECCV 2018



• Video Example: Temporal Coherence of Color

Segment Tracking: Only the first frame is given, colors indicate different instances









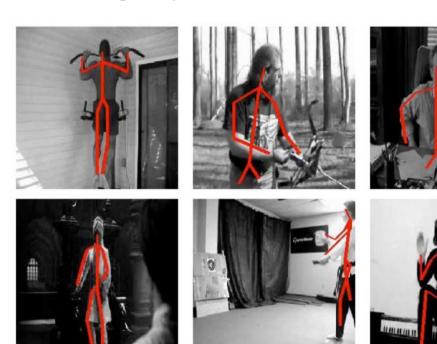






• Video Example: Temporal Coherence of Color

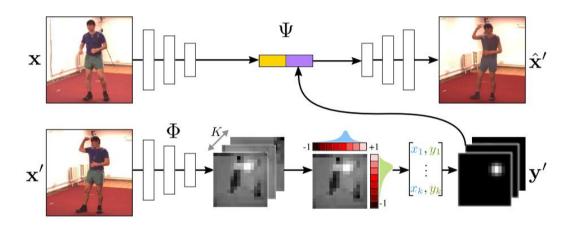
Pose Tracking: Only the skeleton in the first frame is given



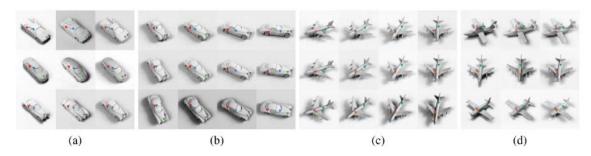


Video Example: Temporal Coherence of Color

Unsupervised Key-point Detection: Only paired images of the same object is given



- Achieve retargeting
- Disentangling Style and Geometry
- Invariant Localization



Unsupervised Learning of Object Landmarks through Conditional Image Generation *Tomas Jakab, Ankush Gupta et al. NIPS, 2018.*



Video + Sound Example

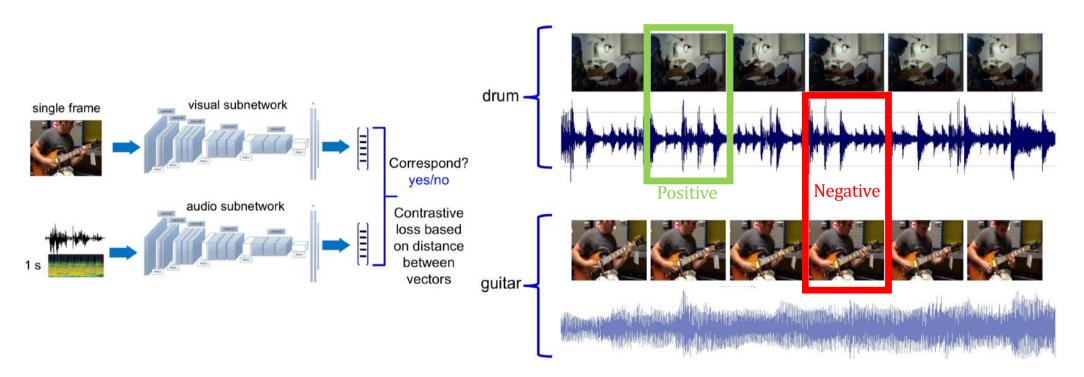


- Sound and frames are:
 - Semantically consistent
 - Synchronized
- Two types of proxy task:
 - Predict audio-visual correspondence
 - Predict audio-visual synchronization



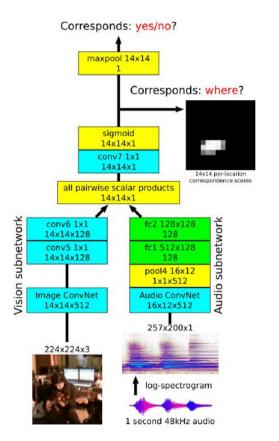
• Video + Sound Example: Audio-Visual Co-supervision

Train a network to predict if image and audio clip correspond





Video + Sound Example: Audio-Visual Co-supervision

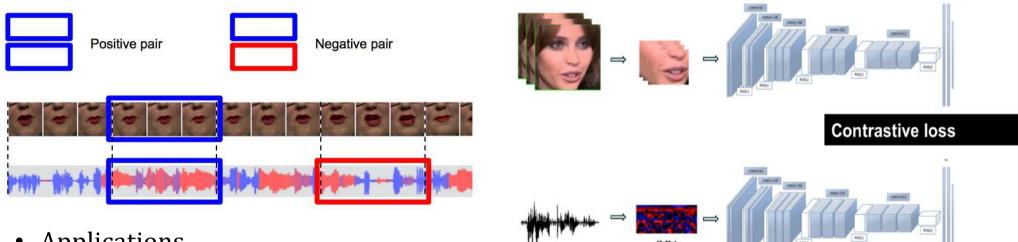


- Learn good visual features
- Learn good audio features
- Learn aligned audio-visual embeddings
- Learn to localize objects that sound
- Using learned features
 - Sound classification
 - Query on image to retrieve audio
 - Localizing objects with sound





Video + Sound Example: Audio-Visual Co-supervision



- Applications
 - Active speaker detection
 - Audio-to-video synchronization
 - Voice-over rejection
 - Visual features for lip reading

Out of time: Automatic lip sync in the wild. Chung, Zisserman, 2016



Self-augmented Learning



Self-augmented Learning

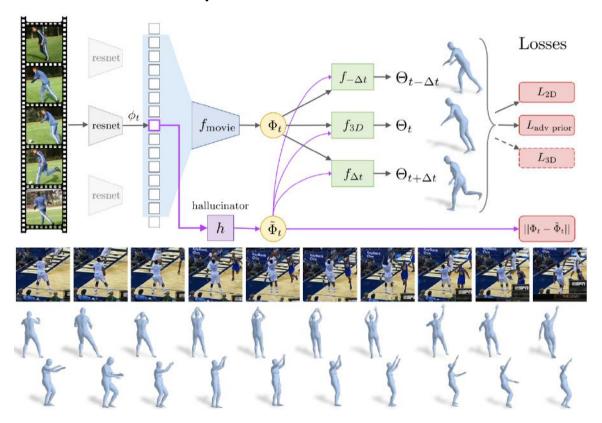
Example: Unsupervised 2D images to 3D shapes

Differentiable 3D to 2D Projector (Known inverse mapping) 2D Discriminators for different views 3D Shapes Multi-projection GAN Generate Estimate view for unlabeled training data images View prediction network



Self-augmented Learning

• Example: 2D Video to 3D shape





Summary



Dual, Self-Supervised, Self-augmented Learnings

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- Dual Learning
- Self-supervised Learning
- Self-augmented Learning



Dual, Self-Supervised, Self-augmented Learnings

- References
 - Dual Learning: A New Learning Paradigm
 https://www.youtube.com/watch?v=HzokNo3g63E
 - DeepMind: Self-supervised Learning
 https://project.inria.fr/paiss/files/2018/07/zisserman-self-supervised.pdf
 - Learning Discrete Representations via Information Maximizing Self-Augmented Training http://proceedings.mlr.press/v70/hu17b/hu17b.pdf



Dual, Self-Supervised, Self-augmented Learnings

- Exercise 1: (Optional)
 - Choice an application and implement it

Link: https://github.com/zsdonghao/deep-learning-note/



Questions?