

Deep Learning 5

Lecture 16: Self-supervised learning and Pseudo-labelling
4F12: Computer Vision

Instructor: Samuel Albanie

Self-supervised Learning - Motivation

Motivation - the state of the (machine perception) nation

Reasons to be cheerful

Deep learning has achieved remarkable progress through the **supervised learning** paradigm:

- Gather a large collection of data and manually **annotate** it
- Supervise a model with the resulting (data, annotation) pairs.

Major gains on vision benchmarks!

Cause for concern

Despite these successes, we still seem to have a long way to go:

- Even the **highest capacity** models trained on the **largest annotated datasets** continue to make "silly" mistakes
- It seems we can never get enough labelled data to get close to the human perception system

Question: Can we take inspiration from the early stages of development of human perception?

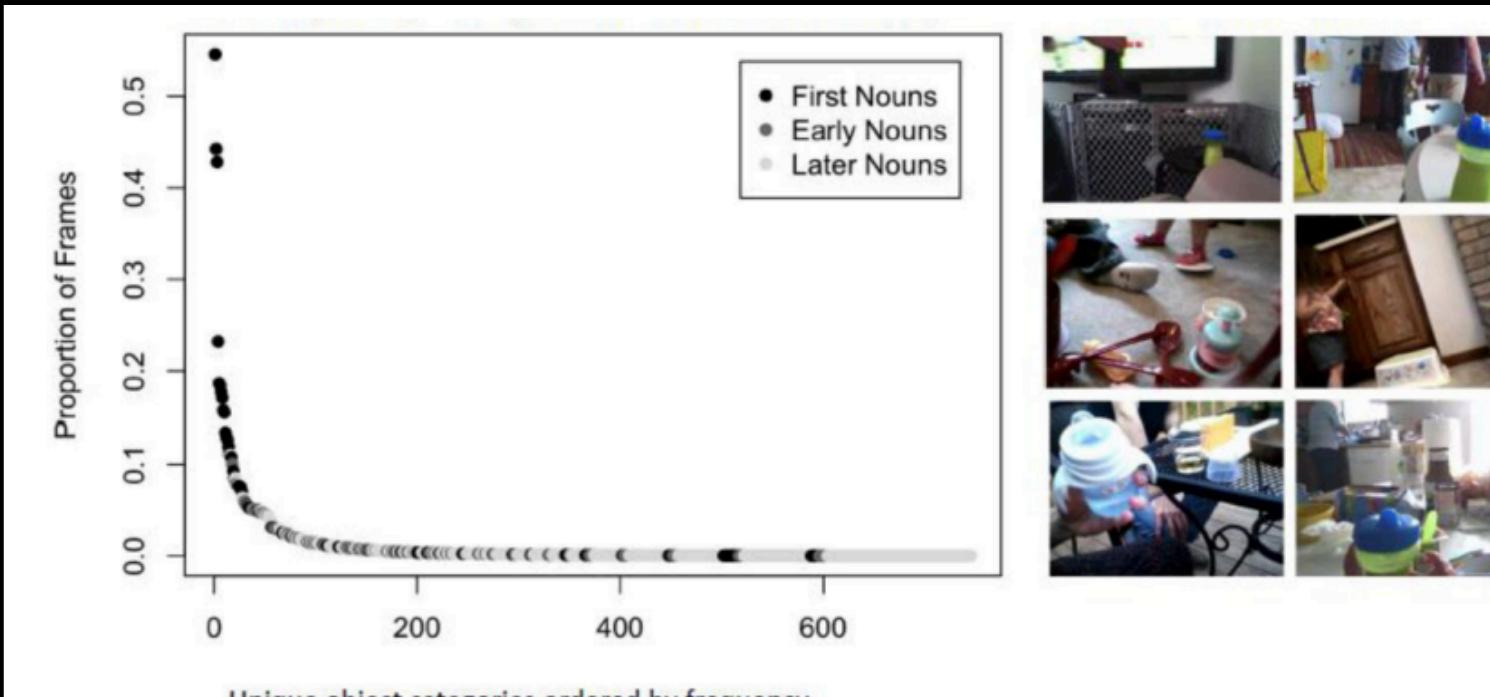
Lessons from Embodied Cognition

Human baby learning is:

- Incremental
- Social
- Physical
- Exploratory
- Language-based
- Multi-modal

We will discuss self-supervised methods that are (partly) inspired by human **multi-modal learning** (exploiting **redundant signal**).

Babies build curricula



Heavy focus on a small number of objects

Practical Challenges

"In order that the machine should have a chance of finding things out for itself it should be allowed to roam the countryside, and the danger to the ordinary citizen would be serious."

Turing, 1948

There are some **practical challenges** to embodied learning.

Simulation may help.

Smith, Linda B. and Michael Gasser. "The Development of Embodied Cognition: Six Lessons from Babies." *Artificial Life* 11 (2005): 13-29.

Figure from Smith, Linda B. et al. "The Developing Infant Creates a Curriculum for Statistical Learning." *Trends in Cognitive Sciences* 22 (2018): 325-336.

Turing, Alan M.. "Intelligent Machinery (1948)." (2004).

Self-supervised Learning - creating your own supervision

Learning via prediction - Helmholtz

Each movement we make by which we alter the appearance of objects should be thought of as an **experiment** designed to test whether we have understood correctly the invariant relations of the phenomena before us, that is, their existence in definite spatial relations.

Helmholtz, 1878

Generate labels by predicting the future

Redundancy provides knowledge - Barlow

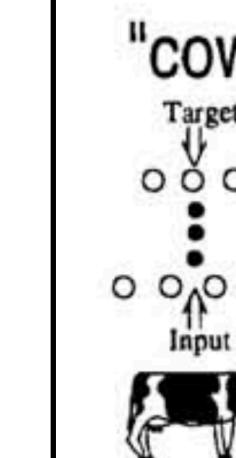
Learning requires previous knowledge: To detect a new association (e.g. event C precedes event U), requires knowledge of the **prior probabilities** of C and U. We can then learn **new associations** as occurrences of C followed by U more frequently than would happen by chance.

Redundancy: To know "**what usually happens**", we need redundancy or "structure" in the input signal (e.g. sensory messages of the same event from different modalities). Redundant signal (by definition) can be predicted from the remaining signal.

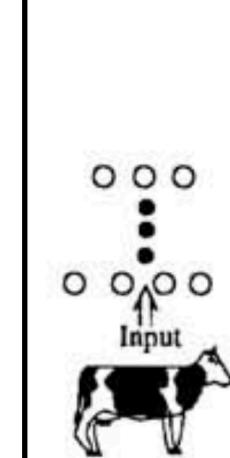
Generate labels from redundant signal

Exploiting Multi-modal Correlation - de Sa

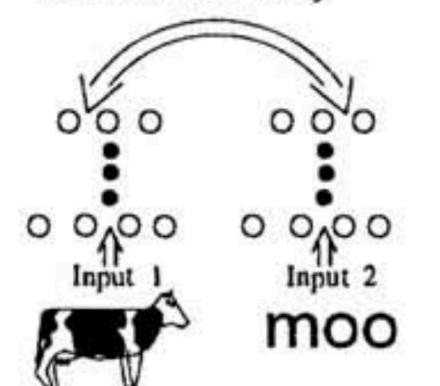
Supervised
- implausible label



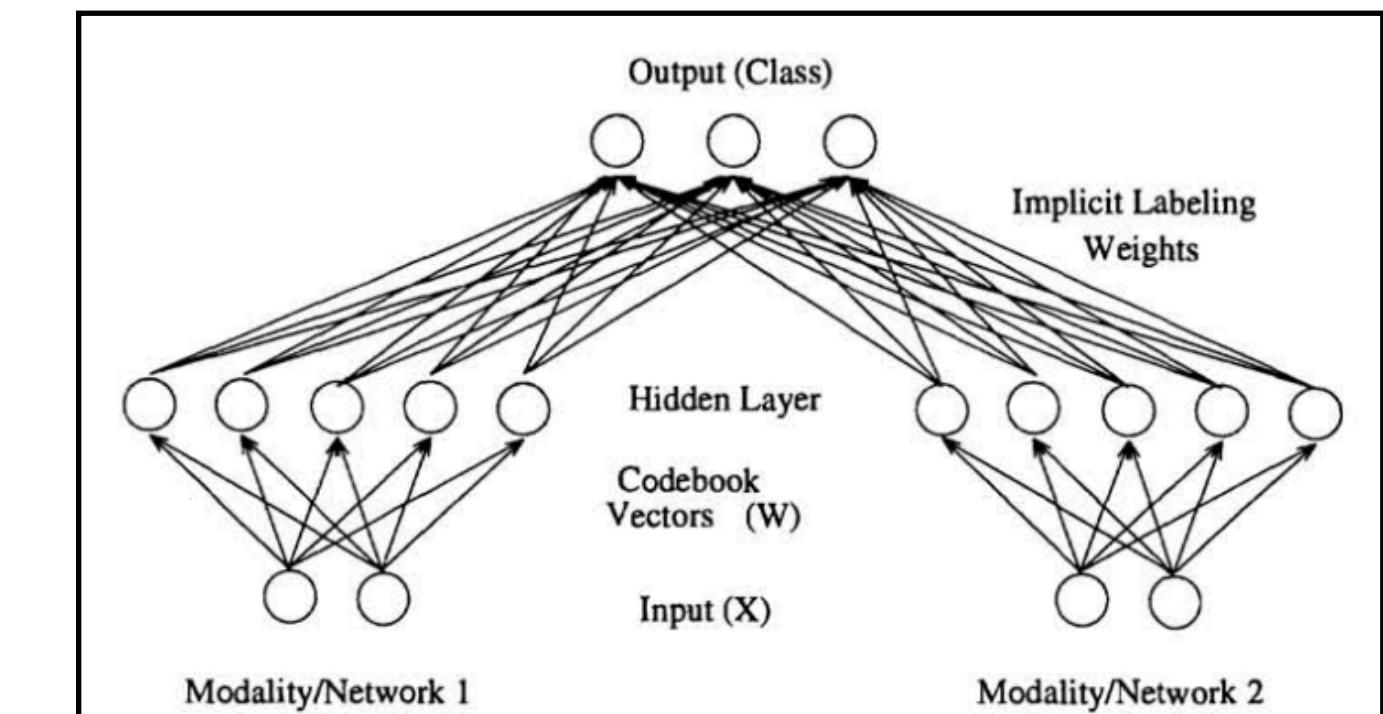
Unsupervised
- limited power



Self-Supervised
- derives label from a co-occurring input to another modality



Learning signal: Minimise **disagreement** between class labels predicted from each modality:



Note: in the modern literature, the distinction between **self-supervised** and **unsupervised** methods can be blurry.

Computational trick: factorial codes for learning new associations

When learning pairwise associations between N events, we need to store N^2 co-occurrence probabilities.

If our representations of events C and U are **statistically independent**, we can compute the chance co-occurrence of C and U from their marginals: i.e. $P(C)P(U)$, so we need only **store N event probabilities!**

Barlow suggested **Minimum Entropy Coding** to obtain such **factorial** representations - but this principle applies more generally.

References:

Helmholtz, Hermann Ludwig Ferdinand von. "The Facts in Perception." (1878)

Barlow, H. B. Unsupervised learning. Neural computation, (1989).

de Sa, Virginia R. "Learning Classification with Unlabeled Data." NeurIPS (1993).

Self-supervised Learning - context as supervision

Natural Language Processing

Unlabelled text corpora have long been used to provide (relatively) low-level supervision for neural networks, with the hope that their distributed representations will enable generalisation.

Autoregressive models

Factor the probability of a sequence, x_1^T , as conditionals:

$$P(x_1^T) = \prod_{t=1}^T P(x_t | x_1^{t-1})$$

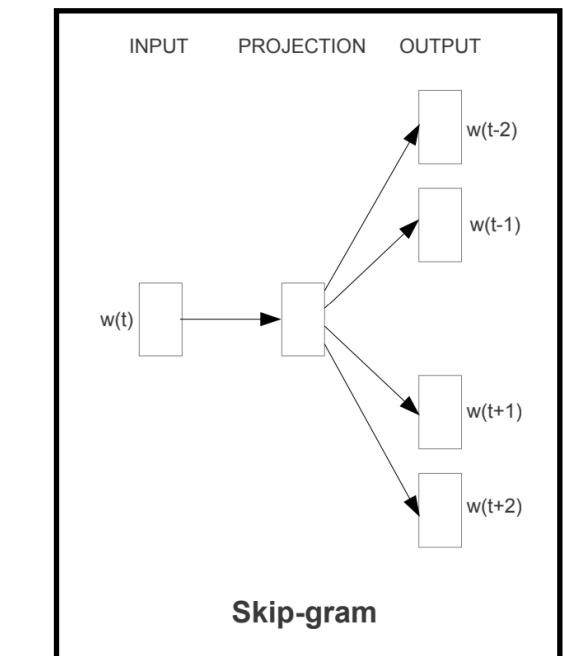
Train a network to maximise likelihood of text corpus.

Predict next character
(Schmidhuber et al., 1996)

Predict next word
(Bengio et al., 2003)

Predicting context

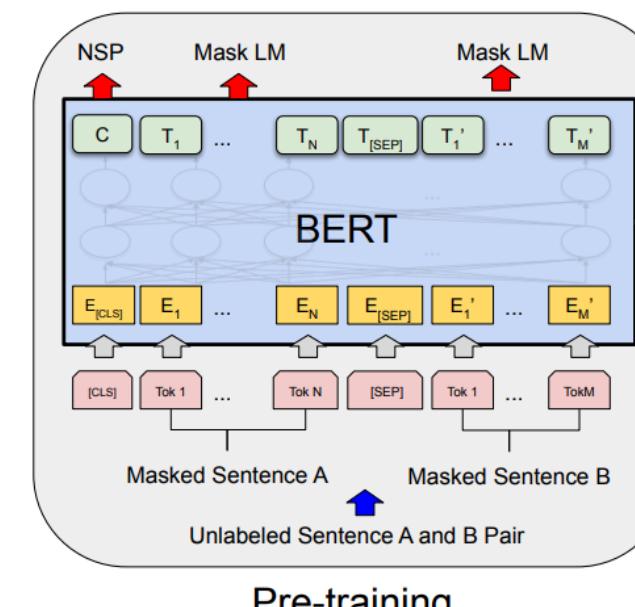
Word2Vec was trained to predict surrounding words.



This work highlighted the critical importance of having lots of training data.

Multitask masking

BERT was trained to predict randomly masked words and next sentence prediction.



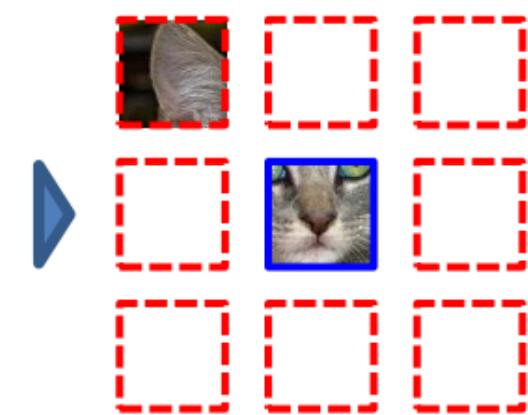
BERT showed the benefits of using a high-capacity bi-directional transformer.

Computer Vision

In vision, we can train the network by tasking it with playing a game (often called a pretext task).

We typically don't care about performance on the pretext task itself, but we hope that by solving it, a model learns good representations of the visual world.

Example:



Question 1:



Question 2:



Key idea: a model can only solve these questions once it learns about cats, buses and trains. **No labelling is required!**

Warning: sometimes the model won't solve the task in the way you wanted!

Doersch et al. found that the network could "cheat" by exploiting chromatic aberration to solve the puzzle unless it was prevented from doing so.

Doersch et al. "Unsupervised Visual Representation Learning by Context Prediction." ICCV (2015)

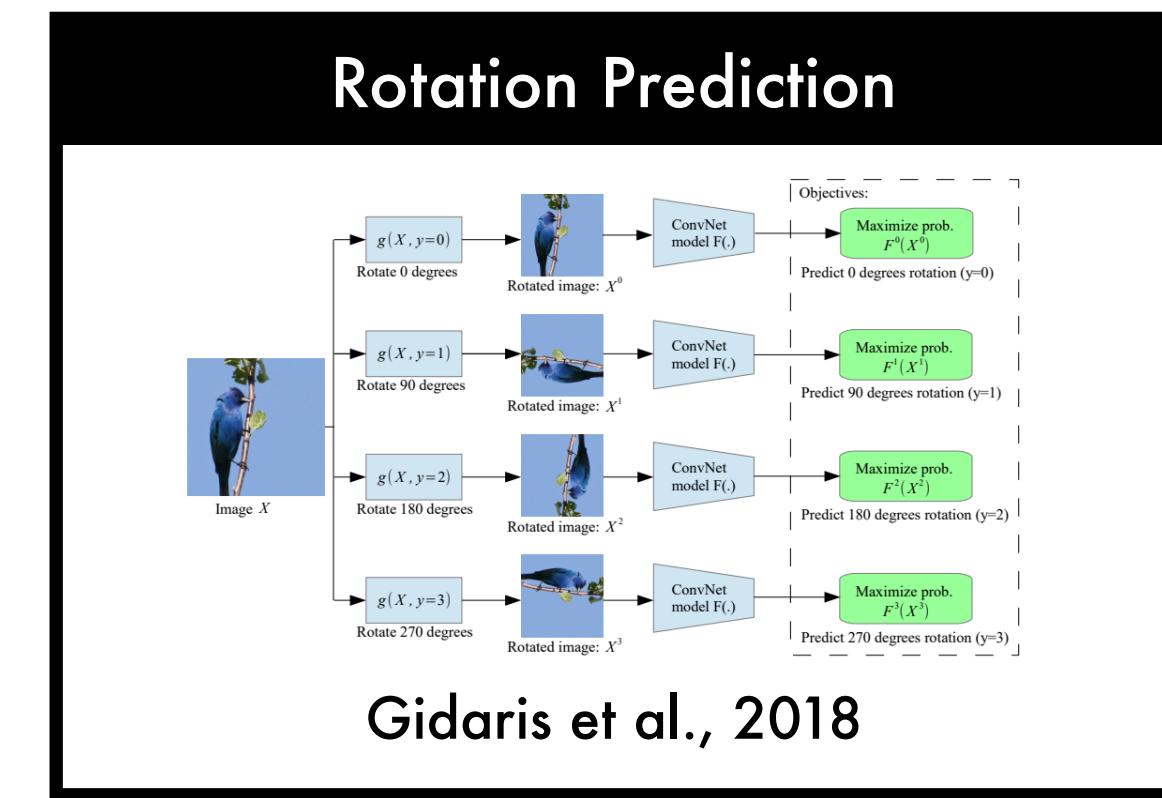
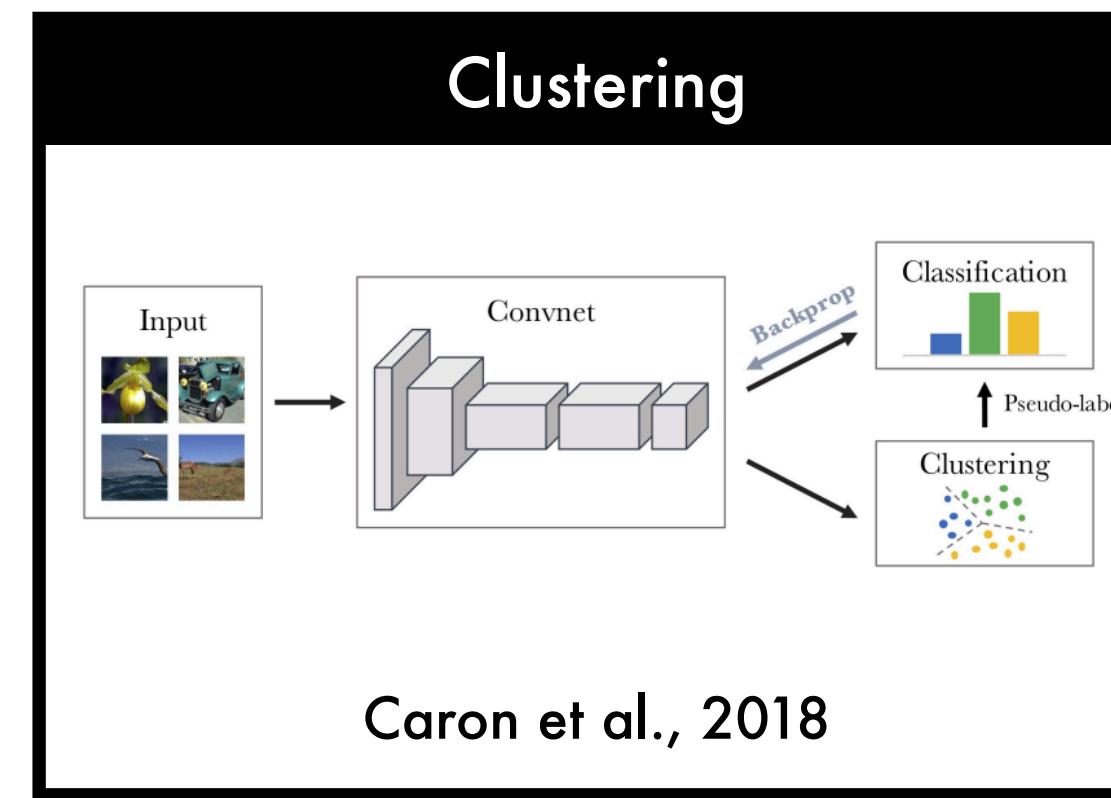
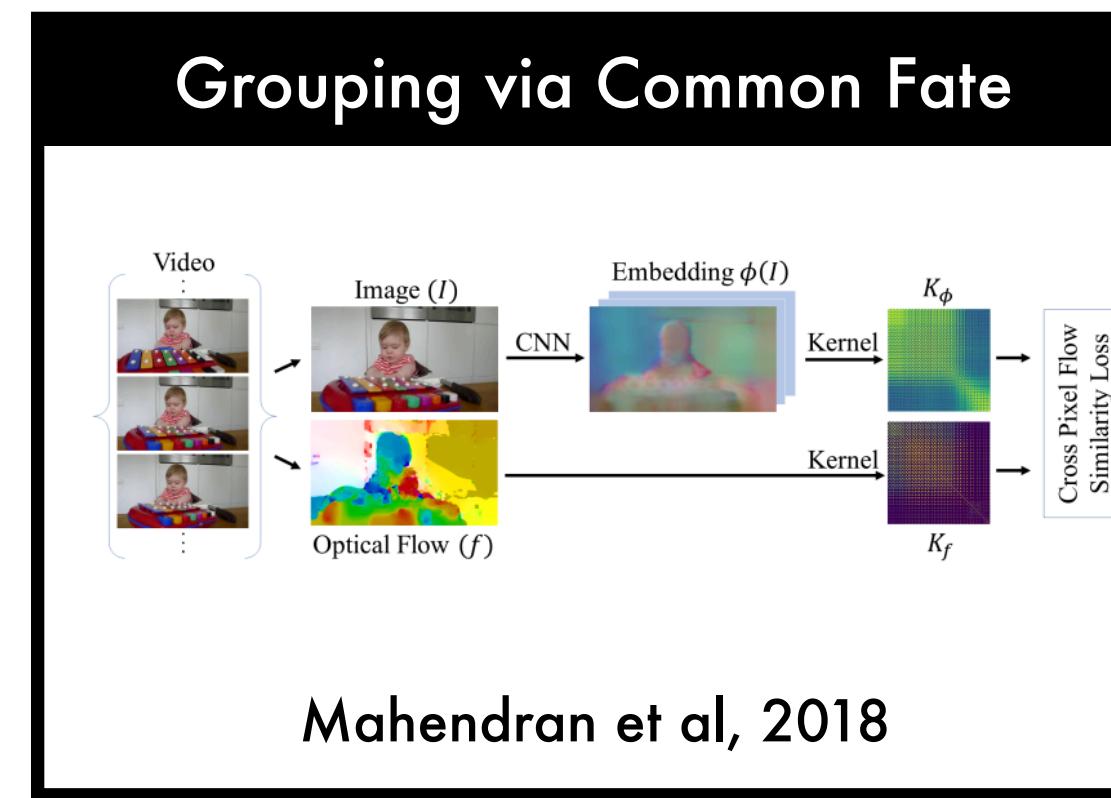
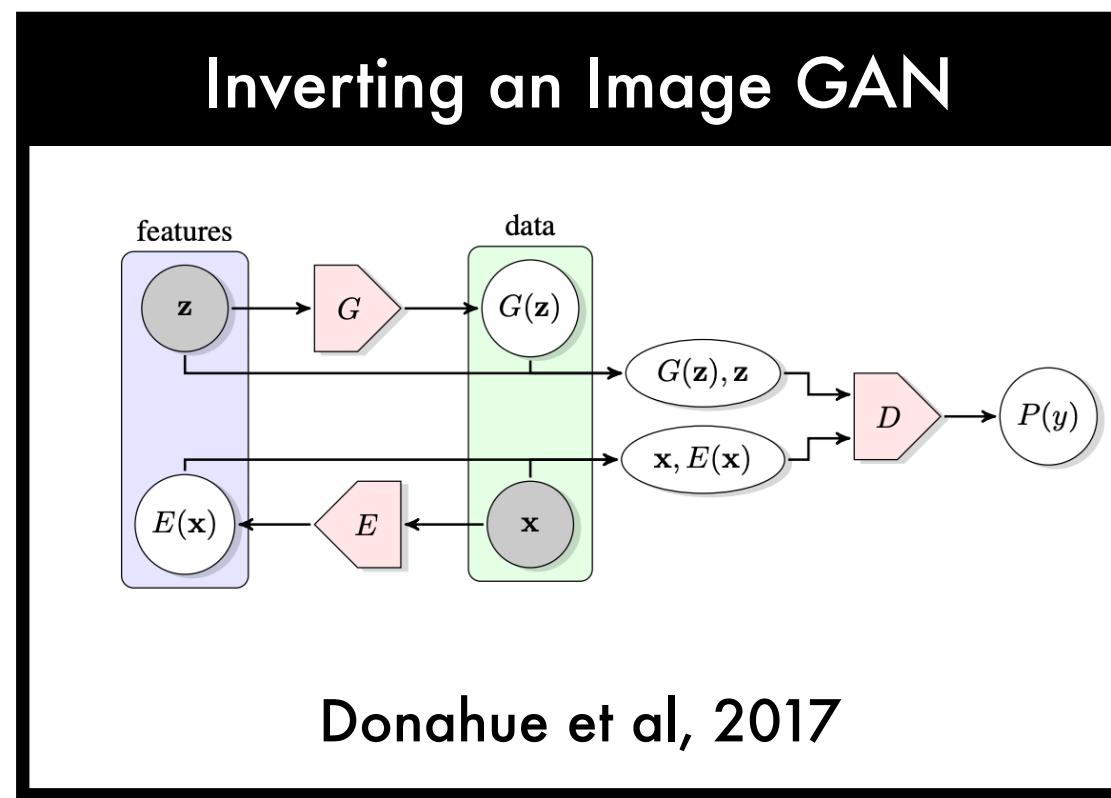
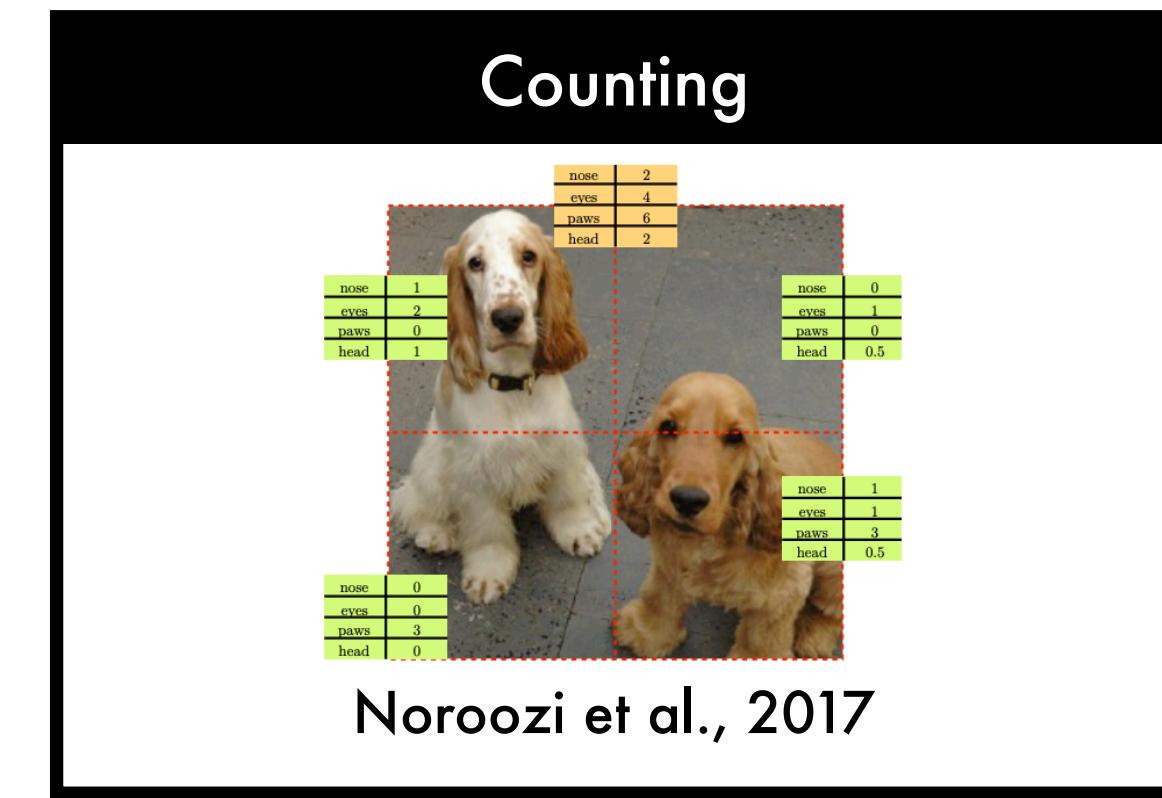
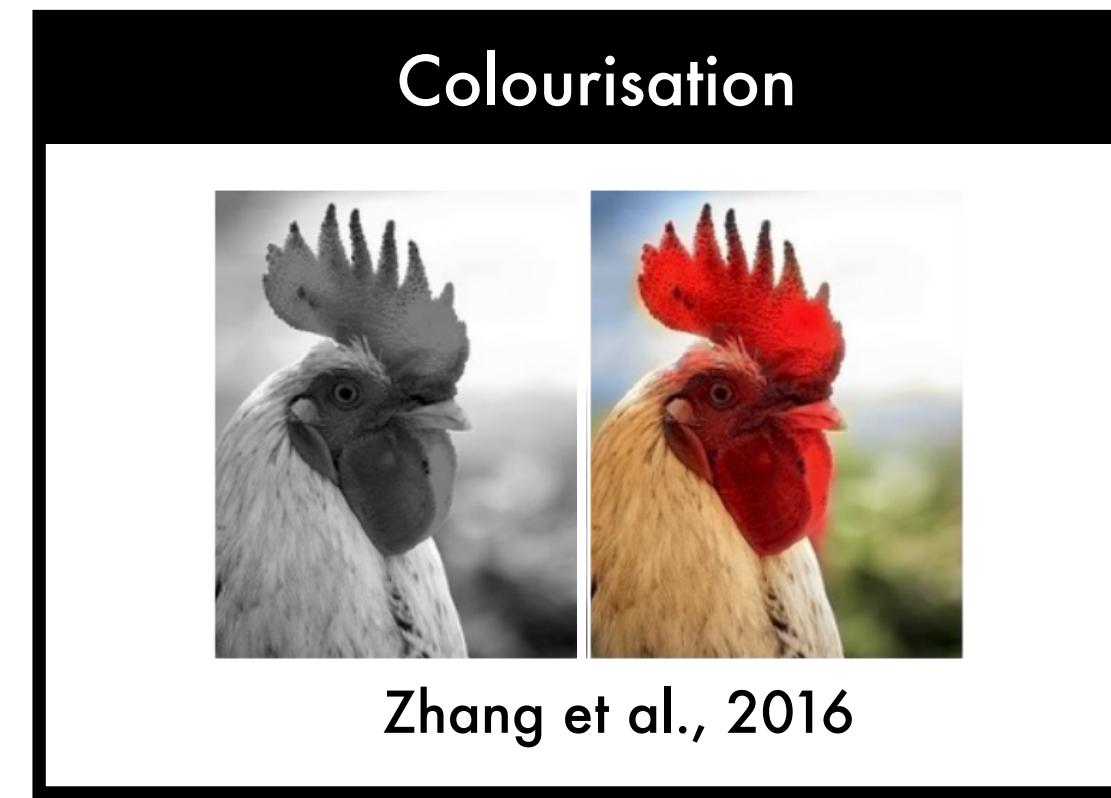
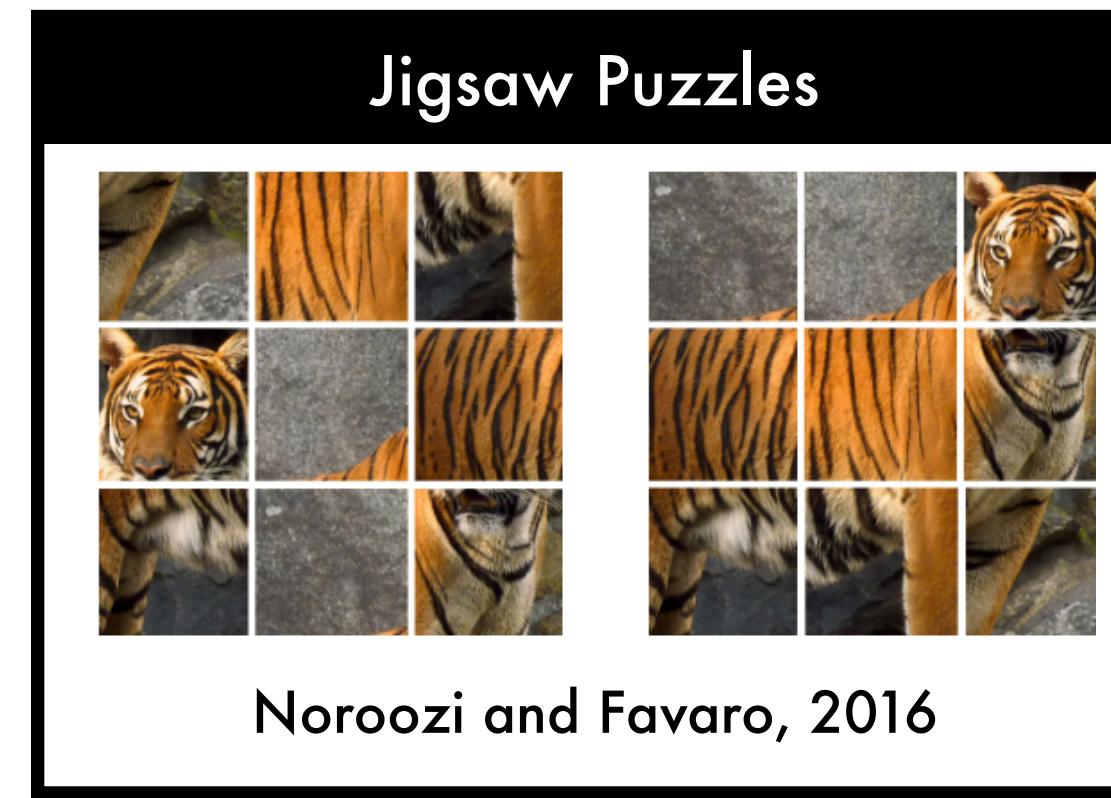
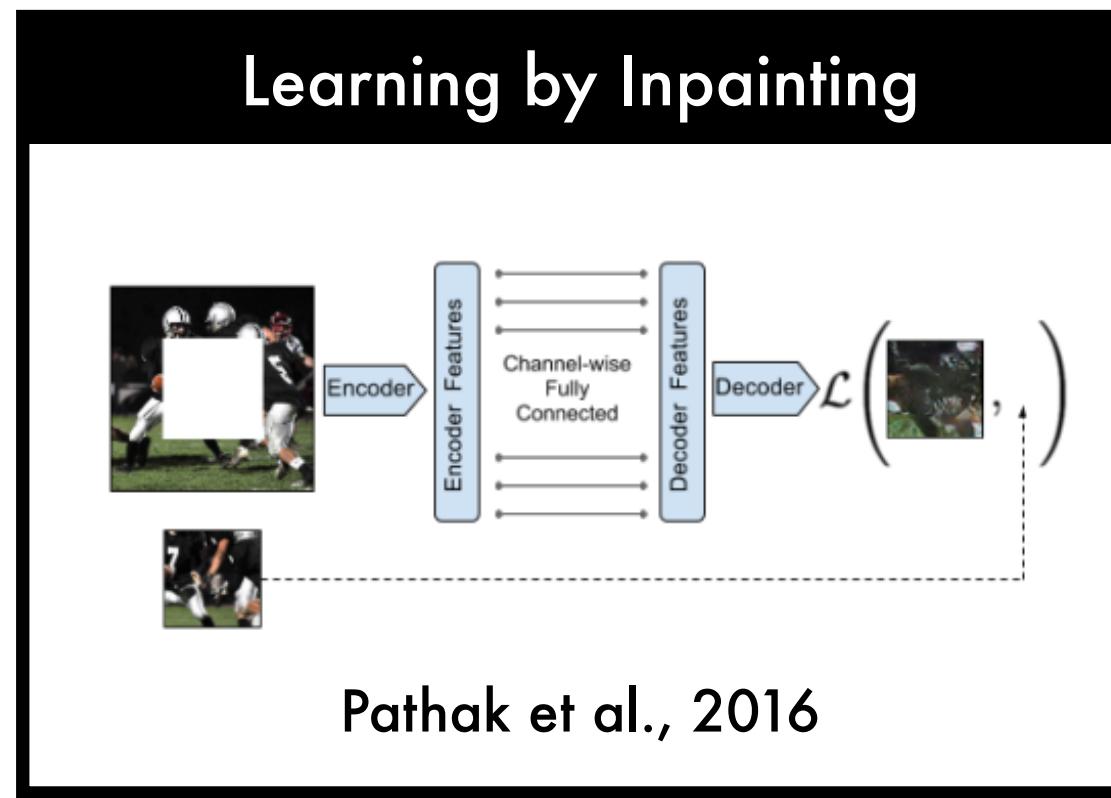
Schmidhuber and Heil. "Sequential neural text compression." IEEE Trans. on neural networks (1996)

Bengio et al. "A Neural Probabilistic Language Model." Journal of Machine Learning Research (2000)

Mikolov et al. "Efficient Estimation of Word Representations in Vector Space." ICLR (2013)

Devlin, et al. "BERT: Pre-training of Deep Bidirectional Transformers for Language Understanding." NAACL (2019)

Self-supervised Learning - pretext tasks



Pathak et al. "Context Encoders: Feature Learning by Inpainting." CVPR 2016

Norooz and Favaro, "Unsupervised Learning of Visual Representations by Solving Jigsaw Puzzles." ECCV (2016)

Zhang et al. "Colorful Image Colorization." ECCV (2016)

Norooz et al. "Representation Learning by Learning to Count." ICCV 2017

Donahue et al. "Adversarial Feature Learning." ICLR 2017

Mahendran et al. "Cross Pixel Optical Flow Similarity for Self-Supervised Learning." ACCV (2018)

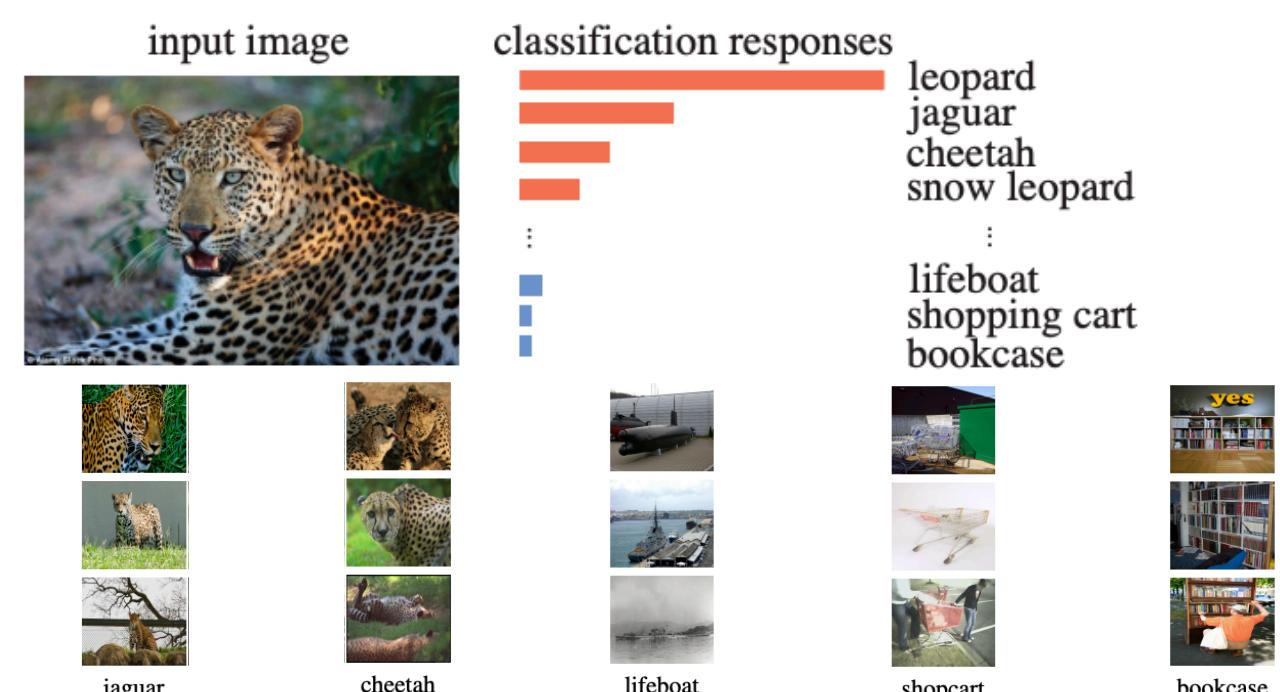
Caron et al. "Deep Clustering for Unsupervised Learning of Visual Features." ECCV (2018)

Gidaris et al. "Unsupervised Representation Learning by Predicting Image Rotations." ICLR 2018

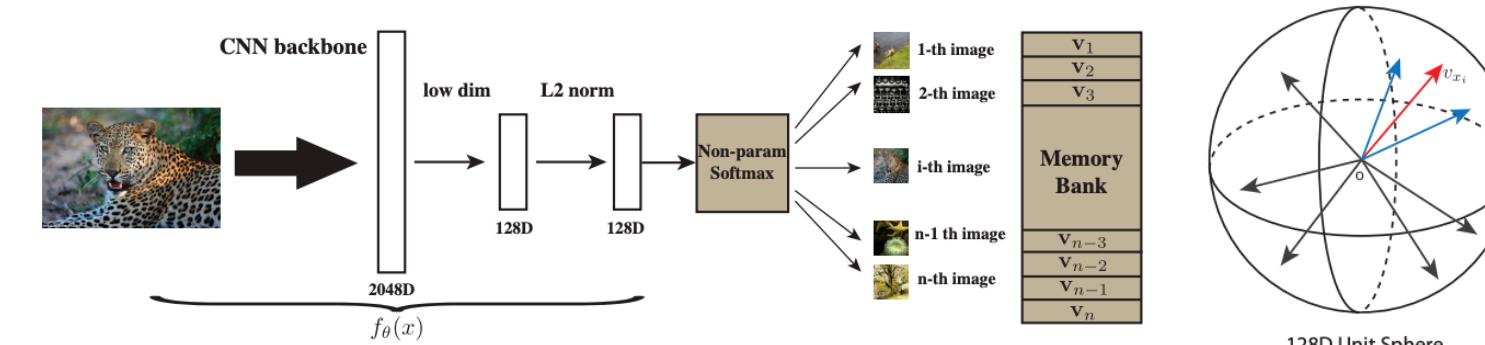
Self-supervised Learning - instance discrimination

Learning via Non-Parametric Instance Discrimination

Motivation: despite training with semantic labels, **fully-supervised** CNNs appear to capture the visual similarity between instances:



Can we learn a representation that captures similarity among instances, by training it to discriminate individual **instances**, rather than semantic classes?



Store instance features in a **memory bank**. Learn to spread them out across a hypersphere.

No labels are required, but strong representations emerge.

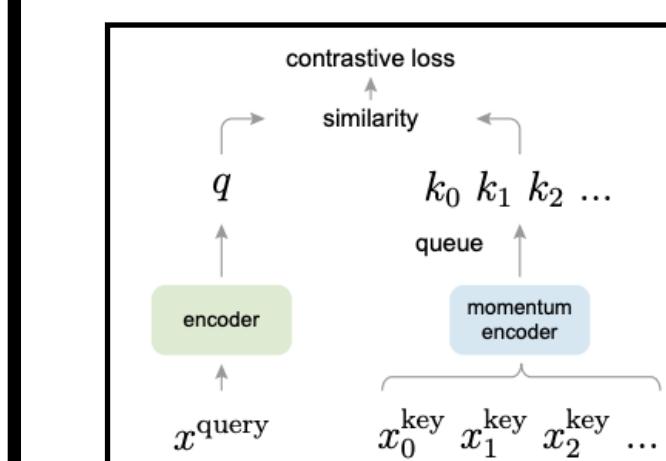
Momentum Contrast

Motivation: Instance discrimination works well, but **memory banks** have an issue:

- Re-computing the feature bank (one feature per image in the dataset) every time the CNN changes is **prohibitively expensive**.
- If memory bank instances are not updated, they grow **increasingly stale** with every optimisation step during training (*suboptimal* for instance discrimination).

MOCO (Momentum Contrast) aims to **avoid staleness** this by:

1. Replacing the memory bank with a **queue of recently encoded samples** (fewer than the full dataset).
2. Encoding queue samples with a **momentum encoder** (a slow moving average of query encoder weights)

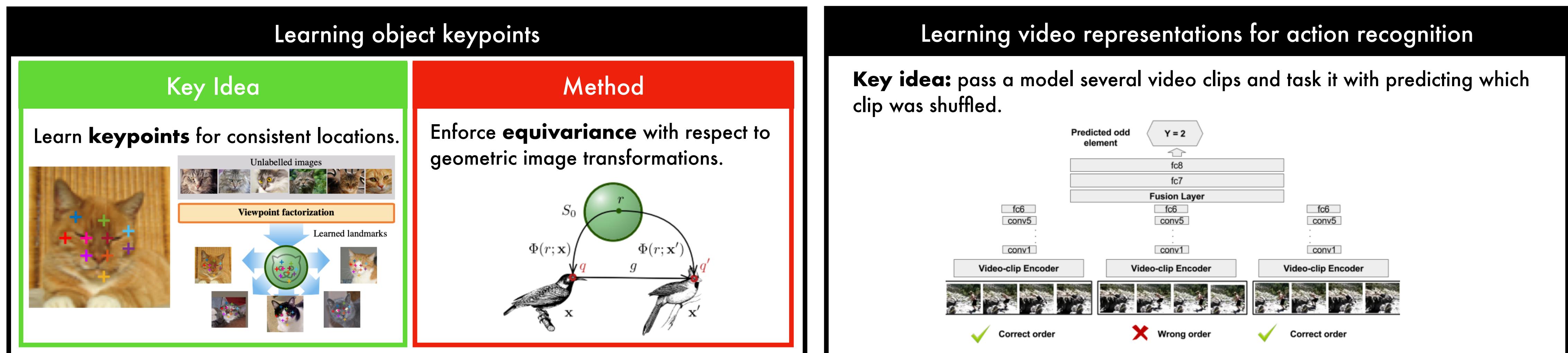
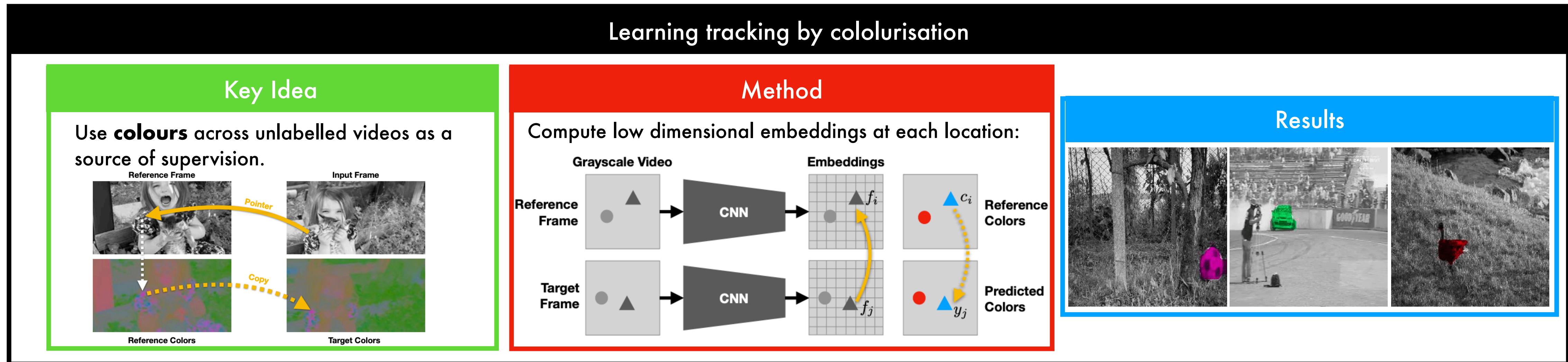


MOCO uses some terminology:

- **"keys"** to refer to instances encoded in the queue with the momentum encoder
- **"queries"** are instances to be compared against keys
- **Positives pairs** - queries and keys originating from the same image.

The **instance discrimination** task is to uniquely match queries against keys that form their positive pairs (optimising an InfoNCE loss). The resulting query encoder then provides a useful representation for **downstream tasks**.

Self-supervised Learning - Beyond Image Representations



Vondrick, Carl et al. "Tracking Emerges by Colorizing Videos." ECCV (2018)

Thewlis et al. "Unsupervised Learning of Object Landmarks by Factorized Spatial Embeddings." ICCV (2017)

Fernando, Basura et al. "Self-Supervised Video Representation Learning with Odd-One-Out Networks." CVPR 2017

Semi-supervised learning and pseudo-labelling

Semi-supervised learning

Semi-supervised learning considers the situation in which the learner has access to both labelled data (typically small in scale) and unlabelled data (typically large in scale).

Pseudo-labelling

Pseudo-labelling (sometimes called "self-training" or "self-labelling") refers to variations of a simple algorithm:

- Train a classifier on the **labelled data**
- Predict the labels of the **unlabelled data** (the resulting predictions are "**pseudo-labels**")
- Retrain the model on the pseudo-labels
- [Optional] re-generate the pseudo-labels, and repeat.

Example: Word sense disambiguation - Yarowsky, 1995

Task: Perform **word sense disambiguation** across a corpus (in this case, for the word "**plant**").

1. Obtain an initial small collection of **labelled samples**, and use them to train a classifier
2. Predict labels for unlabelled instances, retaining those with high confidence (optionally filtering/ expanding the labelled set via automatic heuristics)
3. Repeat until convergence to a final state

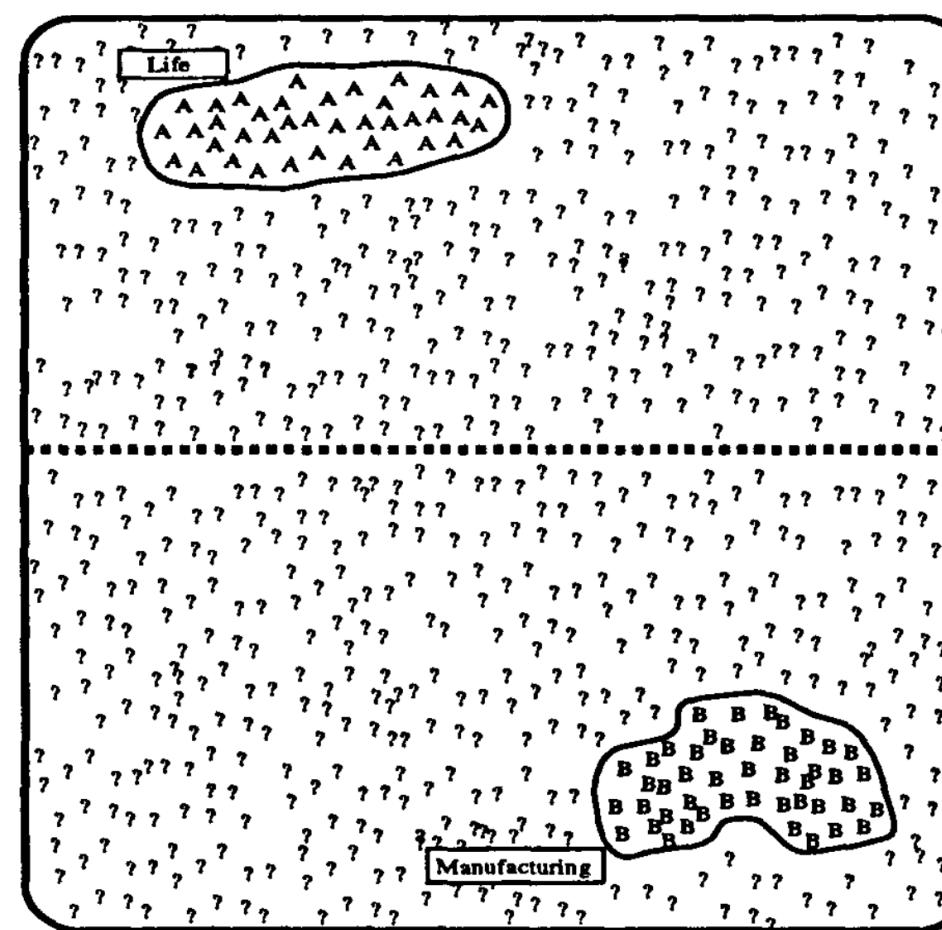


Figure 1: Sample Initial State

A = SENSE-A training example
B = SENSE-B training example
? = currently unclassified training example
Life = Set of training examples containing the collocation "life".

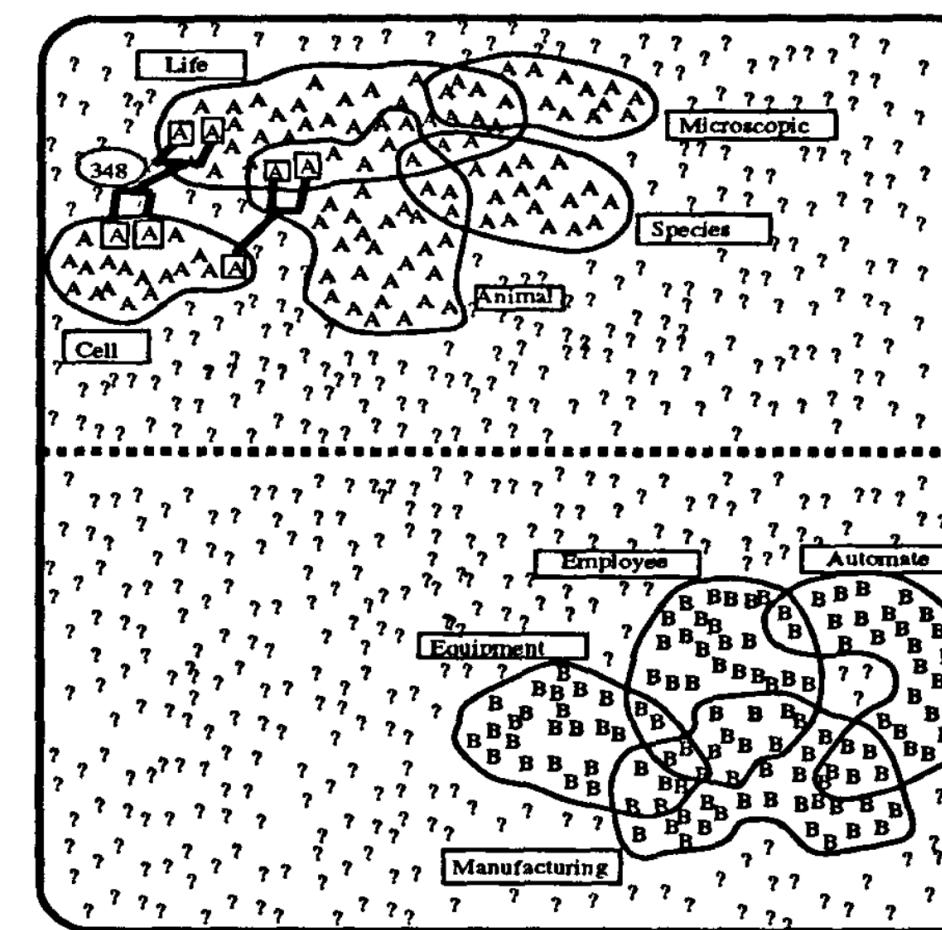


Figure 2: Sample Intermediate State

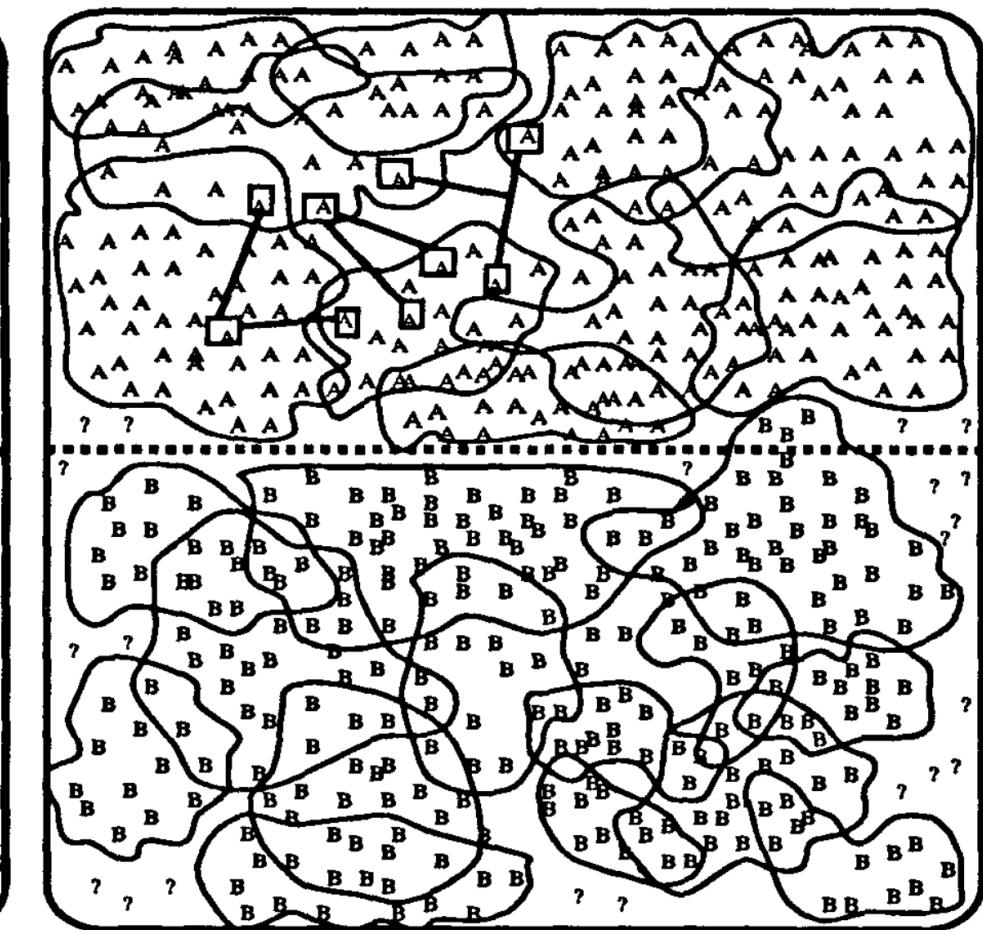


Figure 3: Sample Final State

"It thrives on raw, unannotated monolingual corpora - the more the merrier", Yarowsky

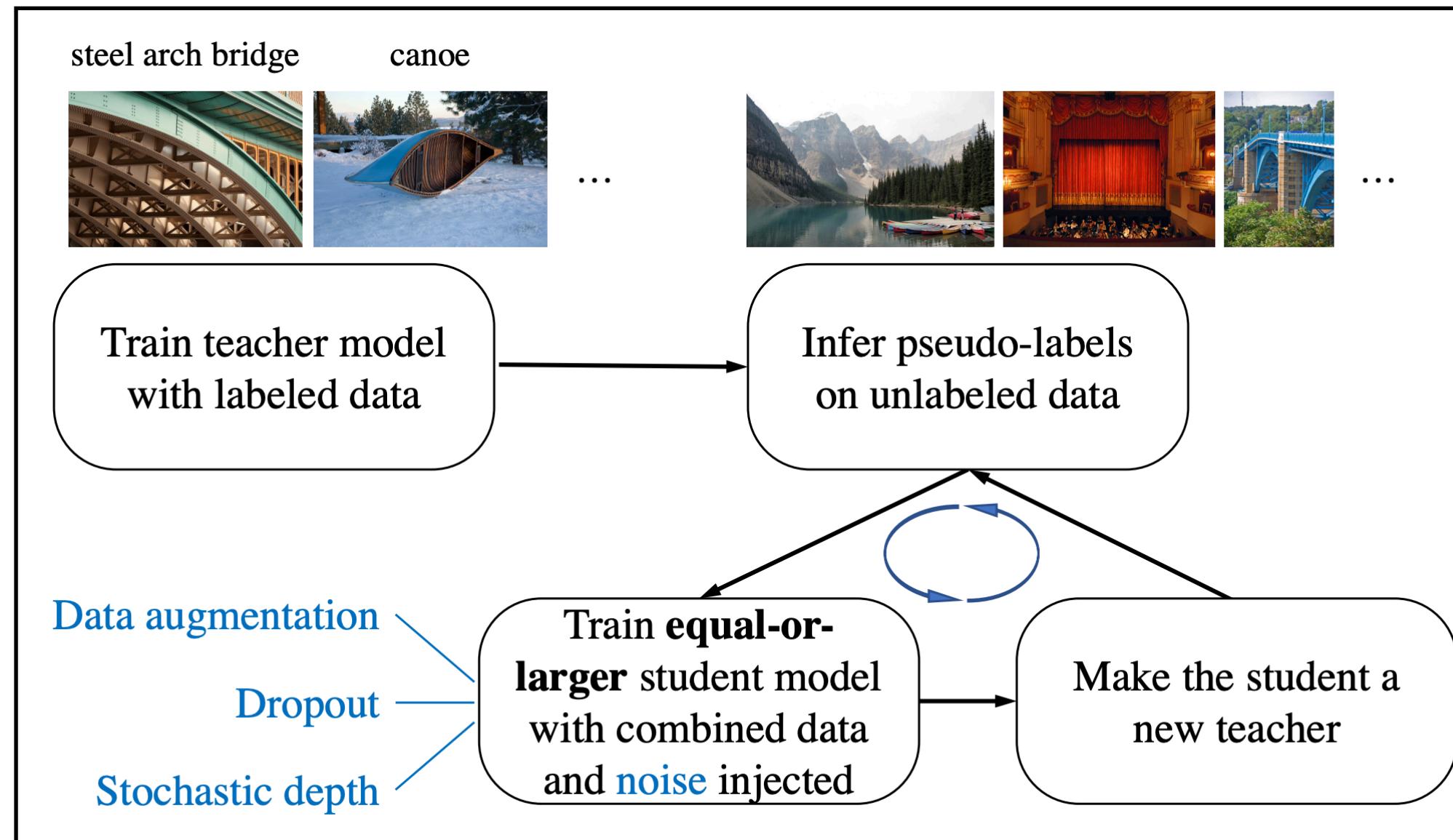
Pseudo-labelling

Self-Training with Noisy Student - Xie 2020

Pseudo-labelling was recently applied to large-scale image classification using:

ImageNet (1M labelled images)

JFT-300M (303M unlabelled images)



This approach achieved significant performance gains over ImageNet-only training.

Pseudo-labelling may become increasingly valuable in future as sensory data grows faster than annotation

End of Lecture 16