ICLR’23 Potpourri

Mert Kilickaya

Notes

Not depth-first, but bread-first

Initial Selection of ~150 papers, then down to best 10

Papers ranked by reviewer scores: Link

Dense Prediction

UNIVERSAL FEW-SHOT LEARNING OF DENSE PREDICTION TASKS

SS: Semantic Segmentation

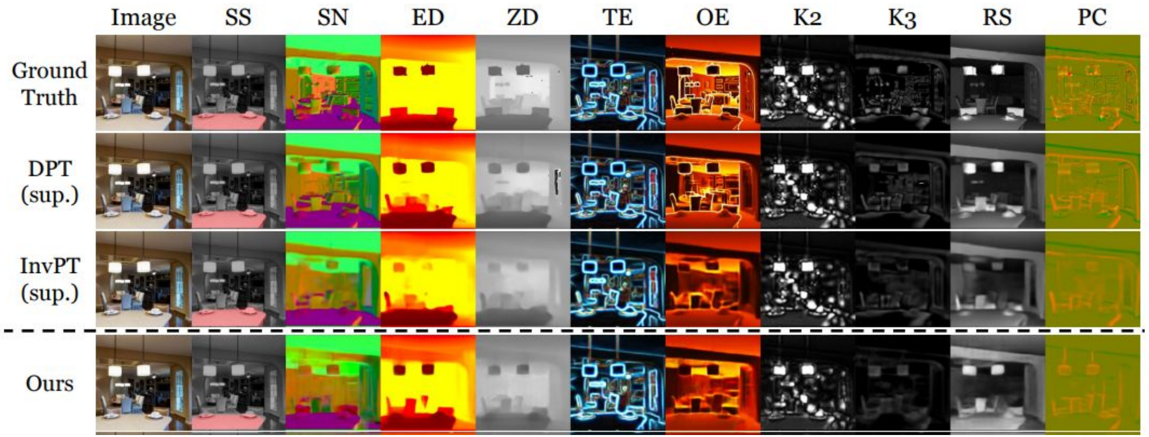
SN: Surface Normal

TE: Texture Edge

OE: Occlusion Edge

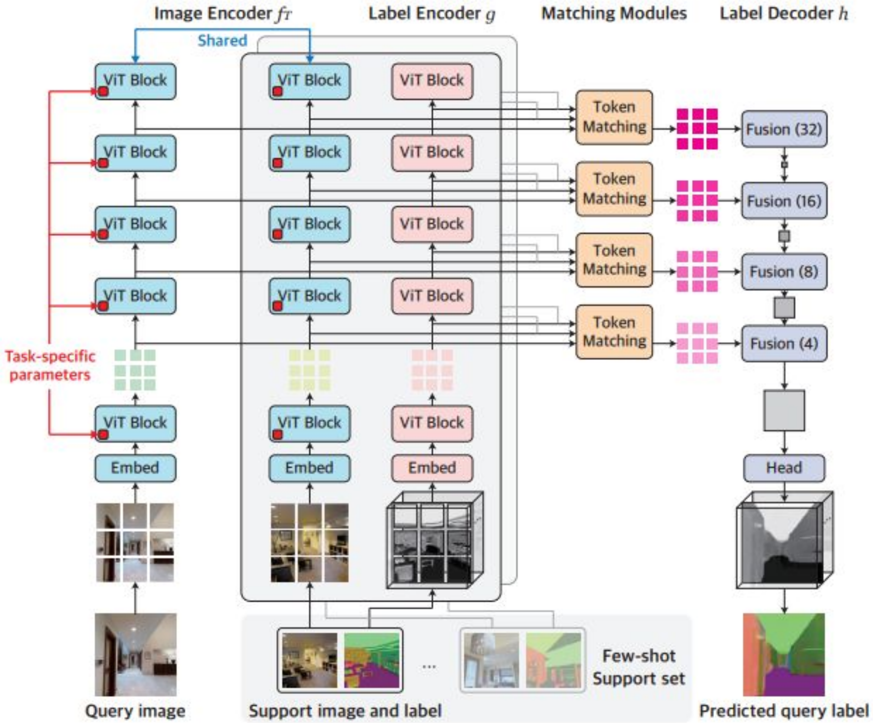
K2: Keypoints

RS: Reshading



What: Train a single model to solve 10 dense prediction tasks simultaneously, with only few-shots

UNIVERSAL FEW-SHOT LEARNING OF DENSE PREDICTION TASKS



How: Train an image encoder + label encoder | Learn to match image patches to label patches (tokens).

VISION TRANSFORMER ADAPTER FOR DENSE PREDICTIONS

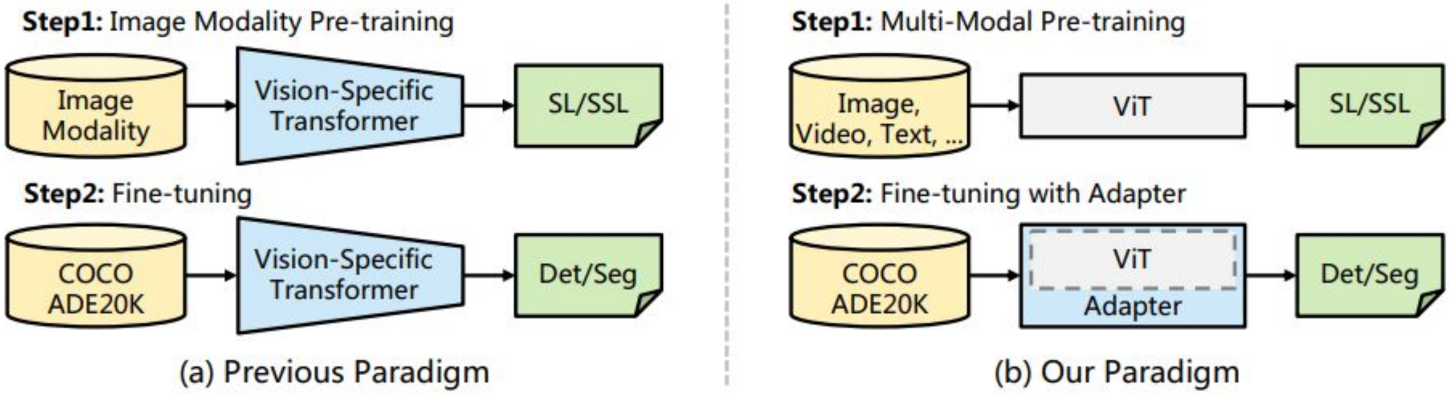


Figure 1: **Previous paradigm *vs.* our paradigm.** (a) Previous paradigm designs vision-specific models and pre-trains on large-scale image datasets via supervised or self-supervised learning and then fine-tunes them on downstream tasks. (b) We propose a pre-training-free adapter to close the performance gap between plain ViT (Dosovitskiy et al., 2020) and vision-specific transformers (*e.g.*, Swin (Liu et al., 2021b)) for dense prediction tasks. Compared to the previous paradigm, our method preserves the flexibility of ViT and thus could benefit from advanced multi-modal pre-training.

What: Do not train separate transformers for recognition/detection, unify them (i.e. plain ViT for localization).

VISION TRANSFORMER ADAPTER FOR DENSE PREDICTIONS

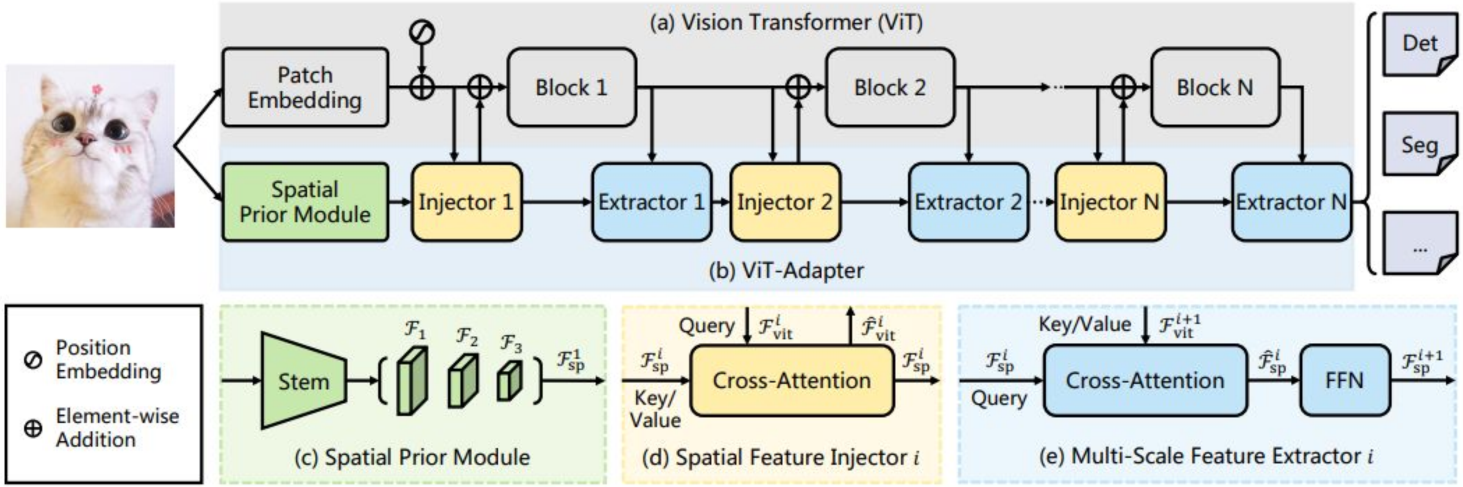
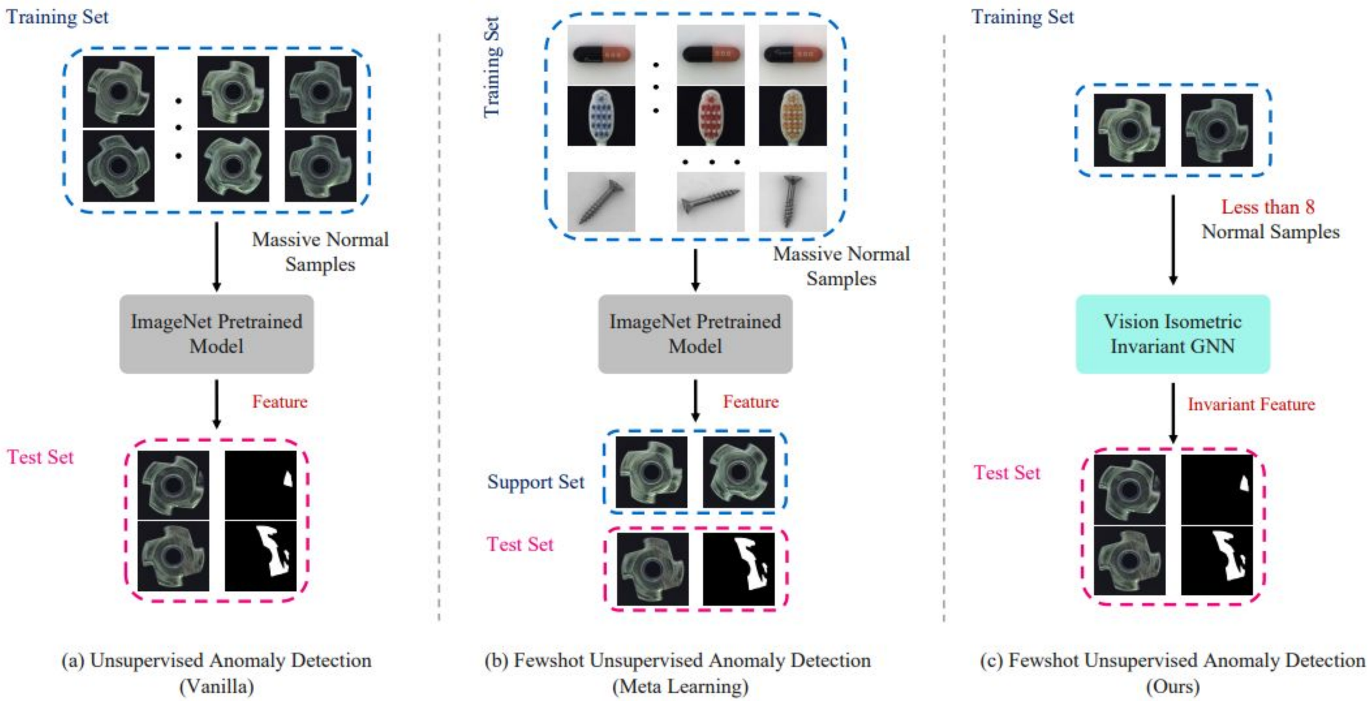


Figure 4: **Overall architecture of ViT-Adapter.** (a) The ViT, whose encoder layers are divided into N (usually $N = 4$) equal blocks for feature interaction. (b) Our ViT-Adapter, which contains three key designs, including (c) a spatial prior module for modeling local spatial contexts from the input image, (d) a spatial feature injector for introducing spatial priors into ViT, and (e) a multi-scale feature extractor for reorganizing multi-scale features from the single-scale features of ViT.

How: Include several blocks to plain ViT (spatial prior module, Extractor/Injector) to perform localization.

PUSHING THE LIMITS OF FEW-SHOT ANOMALY DETECTION IN INDUSTRY VISION: GRAPHCORE



What: For visual anomaly detection, reduce the need for high-volume of normal (non-defect) examples.

PUSHING THE LIMITS OF FEW-SHOT ANOMALY DETECTION IN INDUSTRY VISION: GRAPHCORE

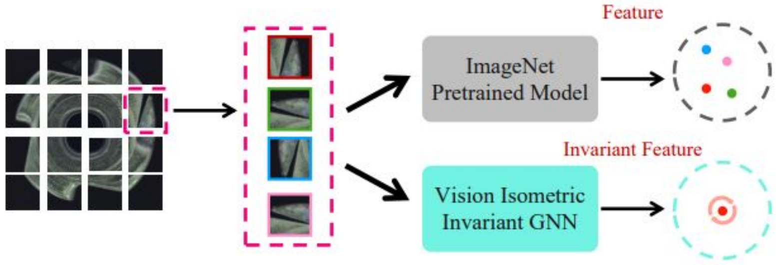


Figure 3: Convolution feature VS vision isometric invariant feature.

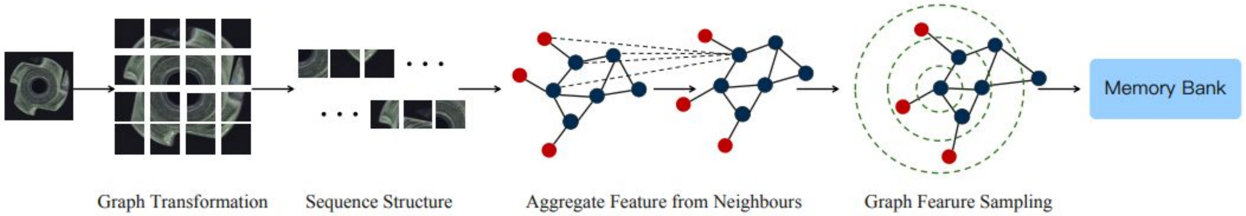


Figure 4: Vision isometric invariant GNN pipeline.

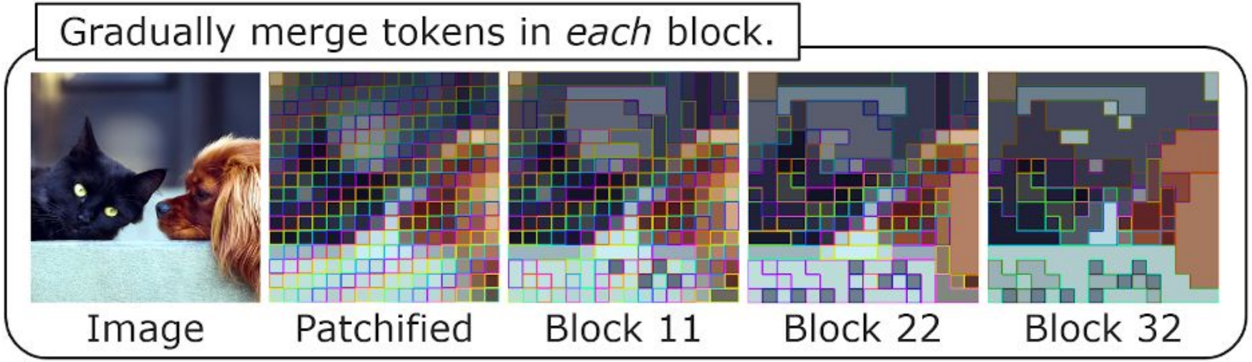
How: Isometric Invariant GNN is strongly invariant to different rotations of the same patch.

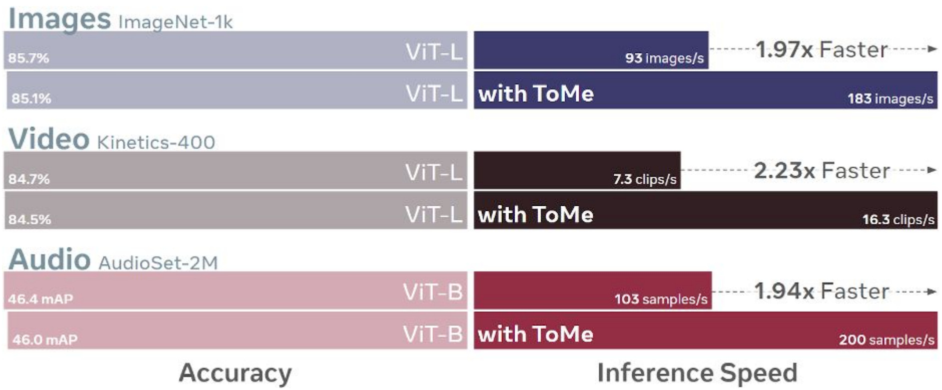
Learning to Learn and Adapt

TOKEN MERGING: YOUR VIT BUT FASTER

What: Learn to group similar tokens in a pre-trained ViT to save inference time *without any further training*.

TOKEN MERGING: YOUR VIT BUT FASTER





How: Measure pairwise similarities across patches -> Merge those with similar features.

[LEARNING TO GROW PRETRAINED MODELS FOR EFFICIENT TRANSFORMER TRAINING]

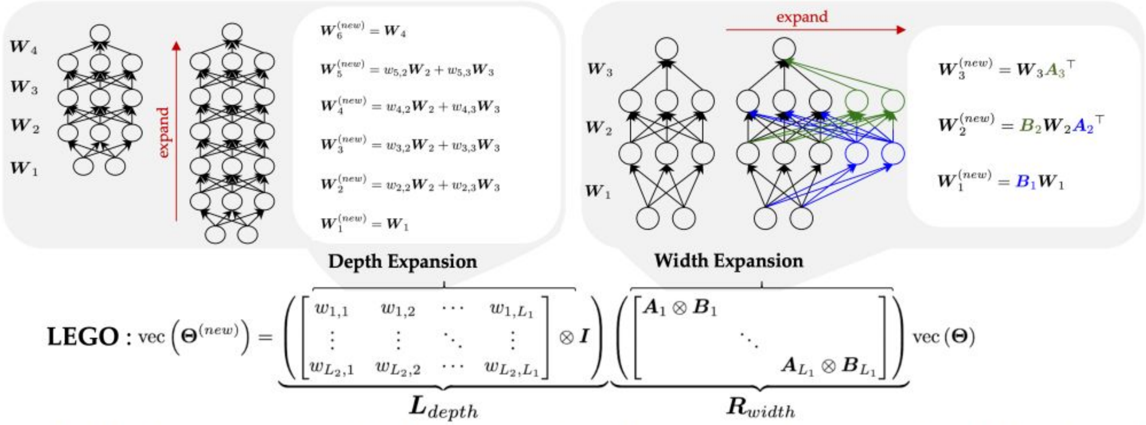


Figure 1: Our learning to grow (LEGO) framework accelerates training by using the weights of a smaller model Θ to initialize the weights of the larger model $\Theta^{(new)}$. The LEGO operator is parameterized as a sparse linear map M that can be decomposed into width- and depth-expansion operators. The width-operator R_{width} and depth-operator L_{depth} are structured matrices obtained from Kronecker products of smaller matrices which encode architectural knowledge by grouping parameters into layers and neurons. While we show the expansion operators for simple multi-layer perceptrons for illustrative purposes, in practice we apply LEGO to enable faster training of transformer networks. In our approach, we learn the LEGO matrix M with a 100 steps of SGD, use this to initialize the larger model, and then continue training as usual. Best viewed in color.

What: Learning to initialize a bigger Transformer with much smaller Transformer (both in depth/width).

LEARNING TO GROW PRETRAINED MODELS FOR EFFICIENT TRANSFORMER TRAINING

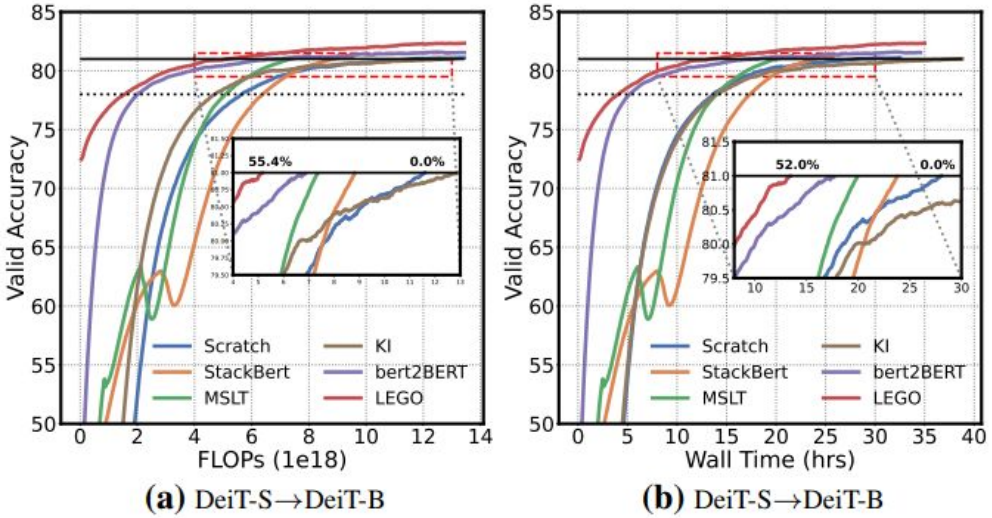


Figure 4: Results on DeiT. (a) accuracy vs. flops and (b) accuracy vs. wall time, for training DeiT-B. LEGO saves flops and wall time by more than 50% over training from scratch on ImageNet.

How: With this learned initialization, a bigger model can be trained <u>50% faster</u> (12 hours vs. 24 hours).

LEARNING TO PREDICT PARAMETER FOR UNSEEN DATA

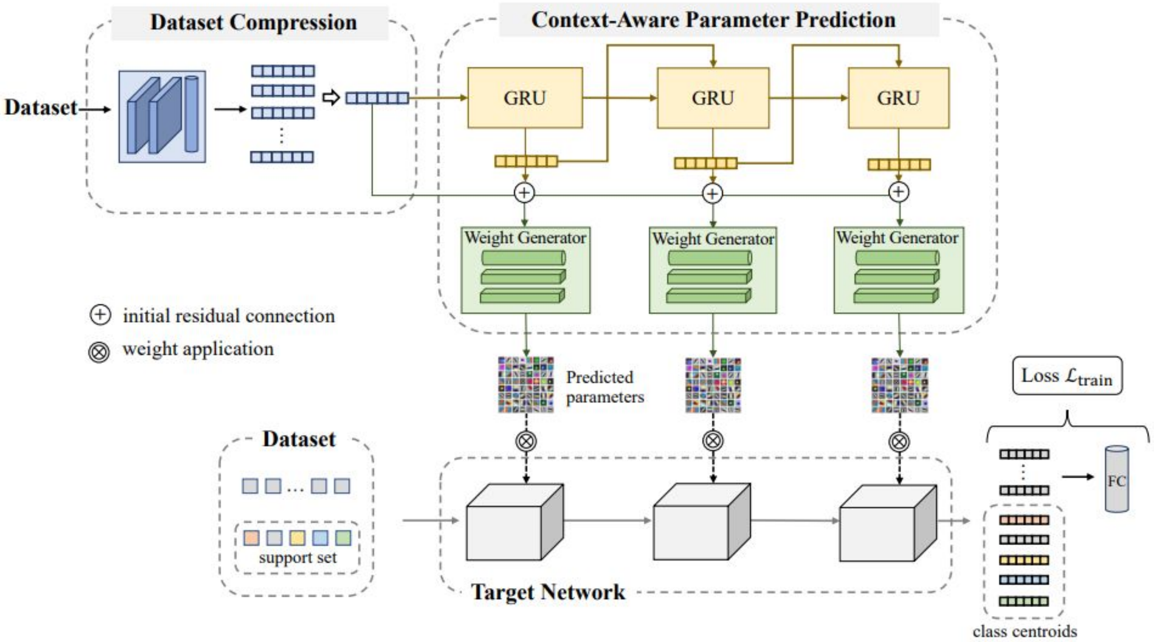


Figure 2: Overview of our proposed PudNet. PudNet first compresses each dataset into a sketch with a fixed size, and then utilizes the hypernetwork to generate parameters of a target network based on the sketch. Finally, PudNet is optimized based on a support set in a meta-learning based manner.

What: Train a hyper-network to generate the weights of another network based on the incoming dataset.

Novel Ideas

UNDERSTANDING SELF-SUPERVISED PRETRAINING WITH PART-AWARE REPRESENTATION LEARNING

Contrastive Self-Supervised Learning

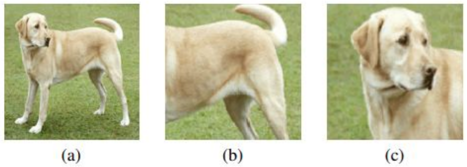
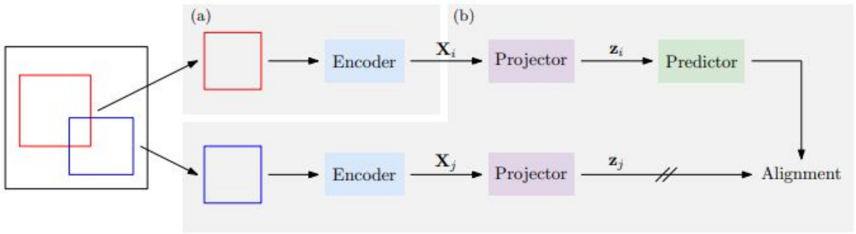


Figure 1: (a) original image, (b-c) two random crops, ar



Masked Image Modelling for Self-Supervised Learning

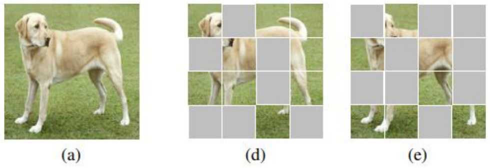
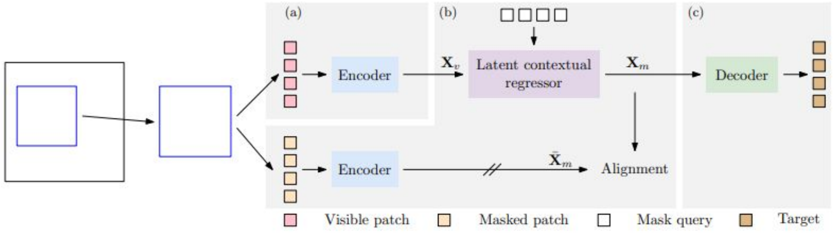
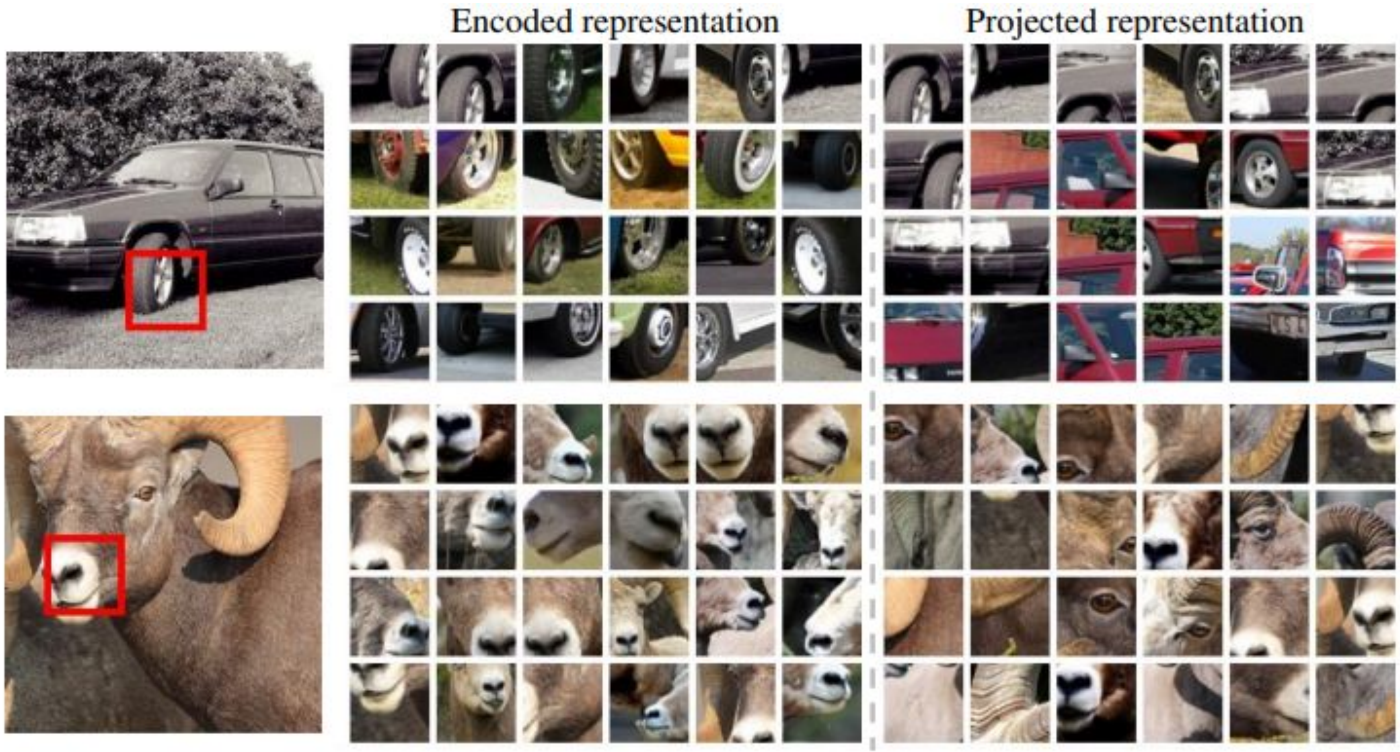


Figure 1: (a) o d (d-e) masked and visible patches.



What: Self-supervised learning models either: 1) Part-to-whole, 2) Whole-to-part representations.

UNDERSTANDING SELF-SUPERVISED PRETRAINING WITH PART-AWARE REPRESENTATION LEARNING



How: See how encoded representation focuses on the same part/projected representation other parts.

LANGUAGE MODELLING WITH PIXELS

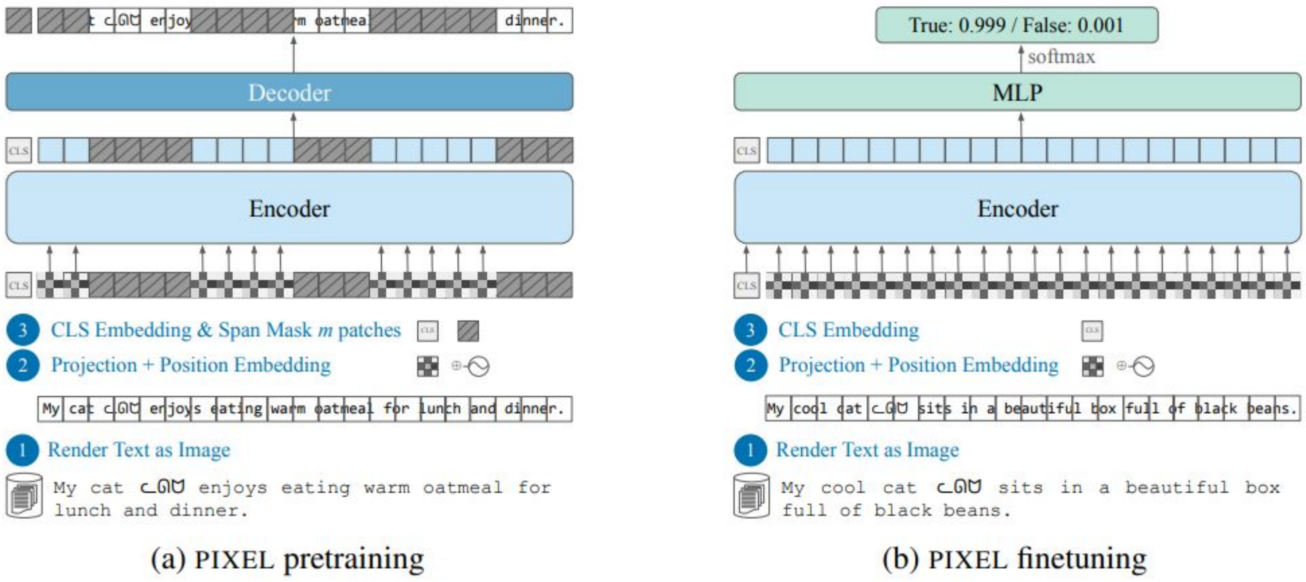
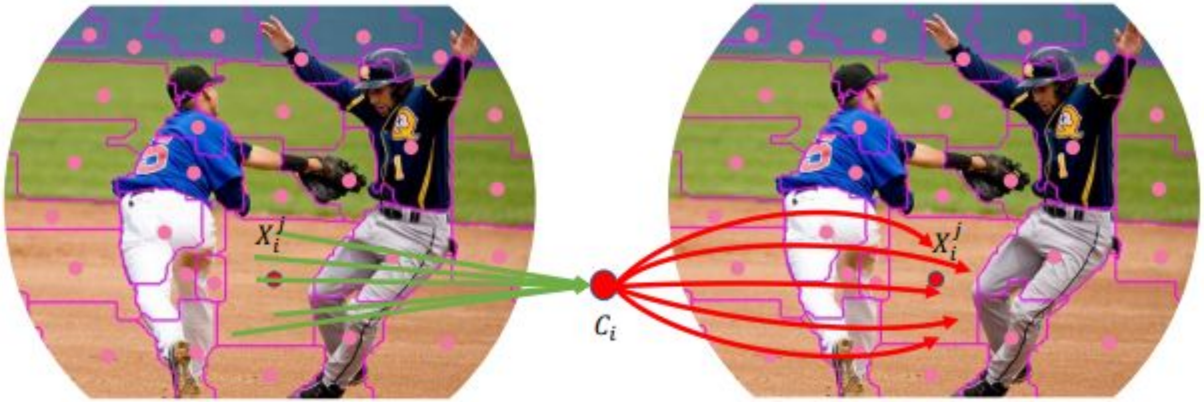


Figure 1: Overview of PIXEL's architecture. Following He et al. (2022), we use a masked autoencoder with a ViT architecture and a lightweight decoder for pretraining (left). At finetuning time (right), the decoder is replaced by a task-specific classification head that sits on top of the encoder.

What: Instead of encoding language as distinct word tokens, just turn them into an image.

Image as Set of Points



What: Instead of processing an input image point-by-point, group similar pixels, and jointly process groups.

Image as Set of Points

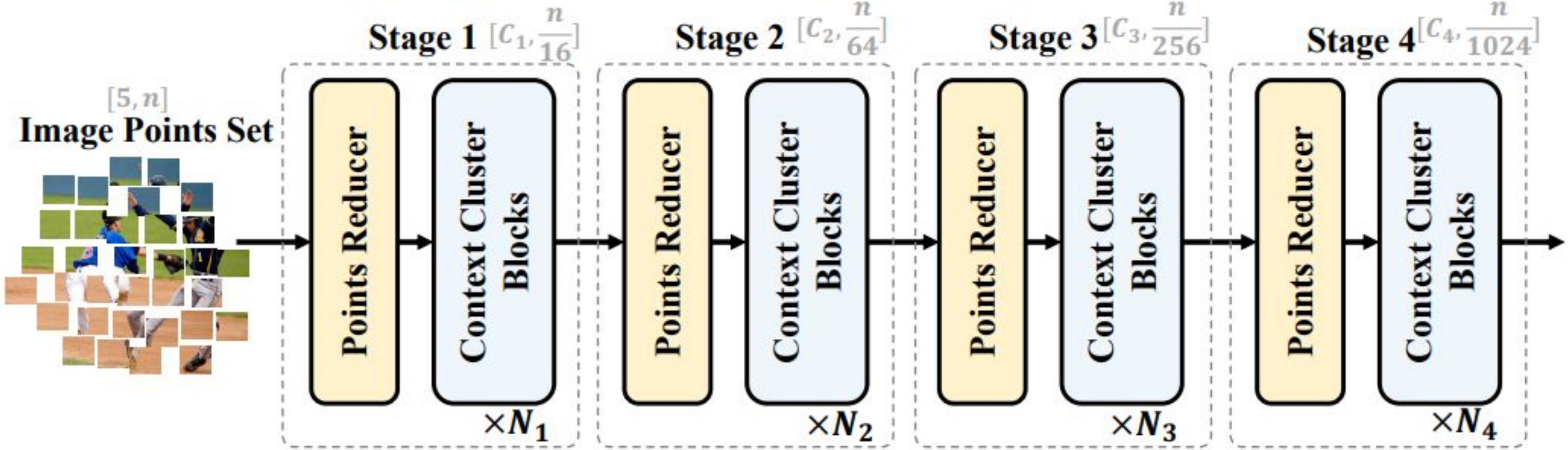
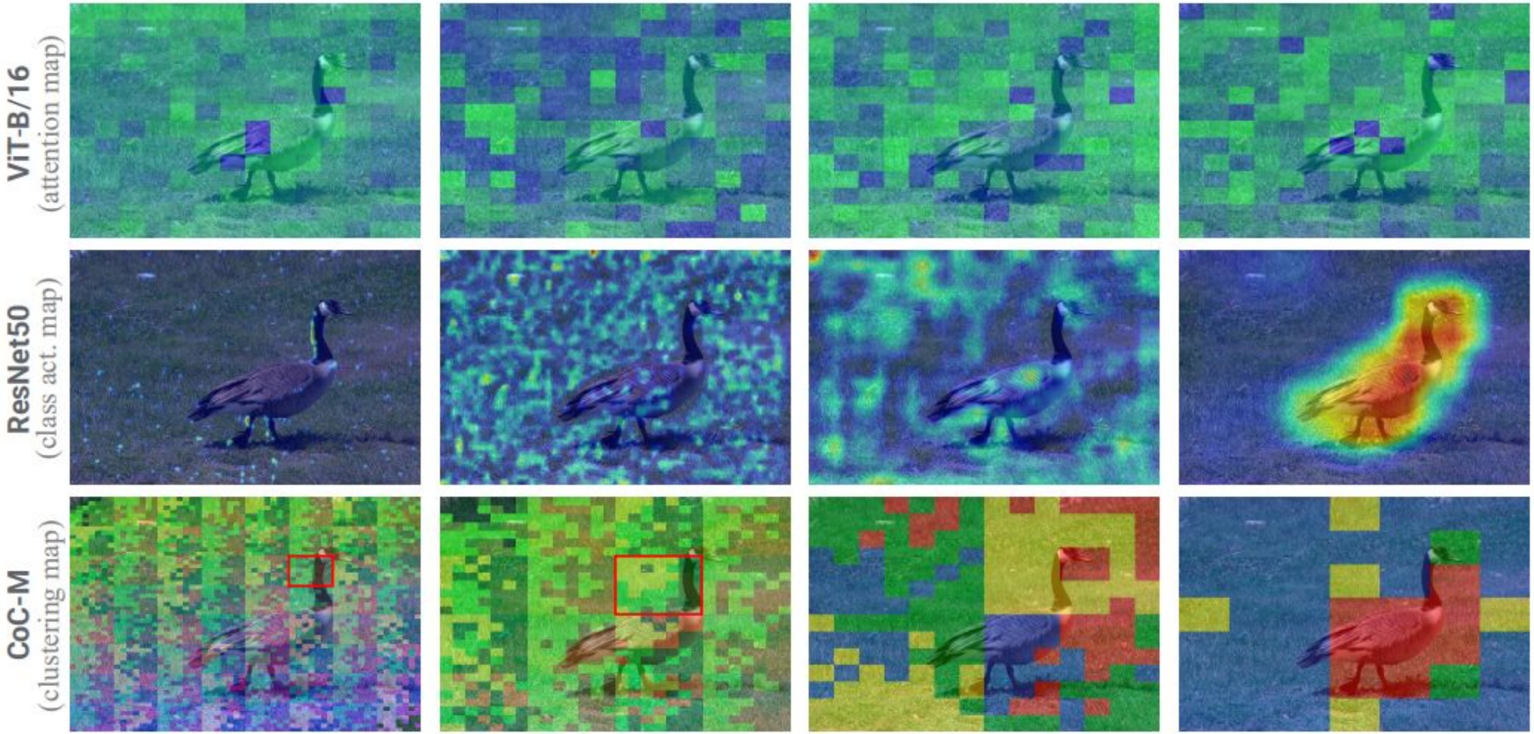


Figure 3: Context Cluster architecture with four stages. Given a set of image points, Context Cluster gradually reduces the point number and extracts deep features. Each stage begins with a points reducer, after which a succession of context cluster blocks is used to extract features.

How: No convolution | No attention | Only clustering blocks + MLP layers | On par performance.

Image as Set of Points



How: See how CoC learns to group (cluster) similar patches together (duck-to-duck, grass-to-grass, etc.)

Discussion

Unification of tasks/models: Converging to single model for all tasks?

Converging to Transformer-like architectures?

Training networks to generate task-specific networks/weights rather than directly tackling tasks?