UNIVERSITY OF TECHNOLOGY
IN THE EUROPEAN CAPITAL OF CULTURE
CHEMNITZ

Neurocomputing

Vision Transformers

Julien Vitay
Professur für Künstliche Intelligenz - Fakultät für Informatik

1 - Vision transformers

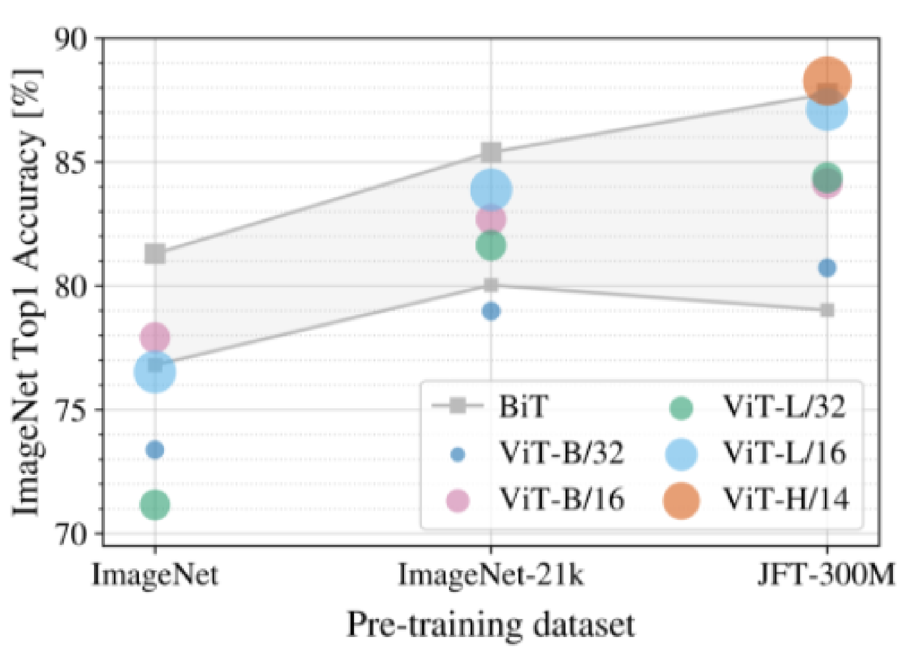
Vision transformer (ViT)

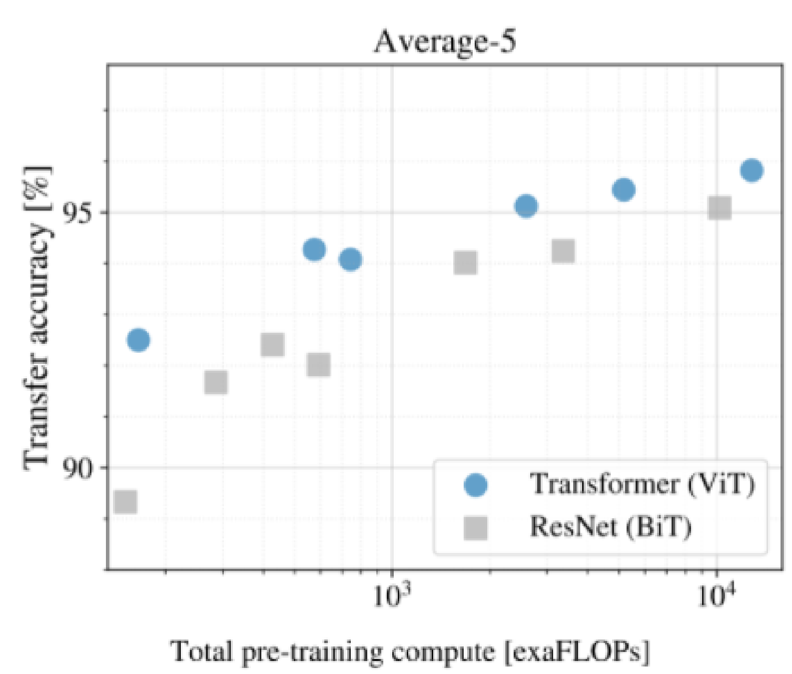
- The transformer architecture can also be applied to computer vision, by splitting images into a **sequence** of small patches (16x16).
- The sequence of patches can then be classified using the first output of the Transformer encoder (BERT) using supervised learning on Imagenet.

Source: https://ai.googleblog.com/2020/12/transformers-for-image-recognition-at.html

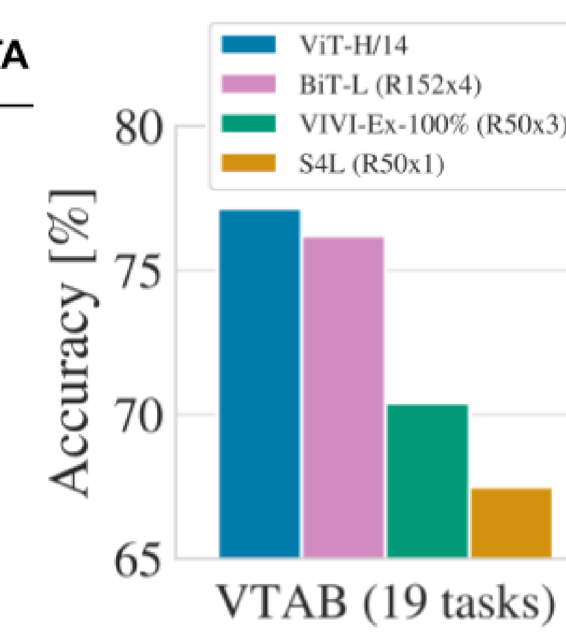
Vision transformer (ViT)

- The Vision Transformer (ViT) outperforms state-of-the-art CNNs on Imagenet while requiring less computations (Flops), but only when pretrained on bigger datasets.
- The performance is acceptable when trained on ImageNet (1M images), great when pre-trained on ImageNet-21k (14M images), and state-of-the-art when pre-trained on Google's internal JFT-300M dataset (300M images).
- Transfer learning on smaller datasets is also SotA.





	ViT-H	Previous SOTA
ImageNet	88.55	88.5
ImageNet-ReaL	90.72	90.55
Cifar-10	99.50	99.37
Cifar-100	94.55	93.51
Pets	97.56	96.62
Flowers	99.68	99.63

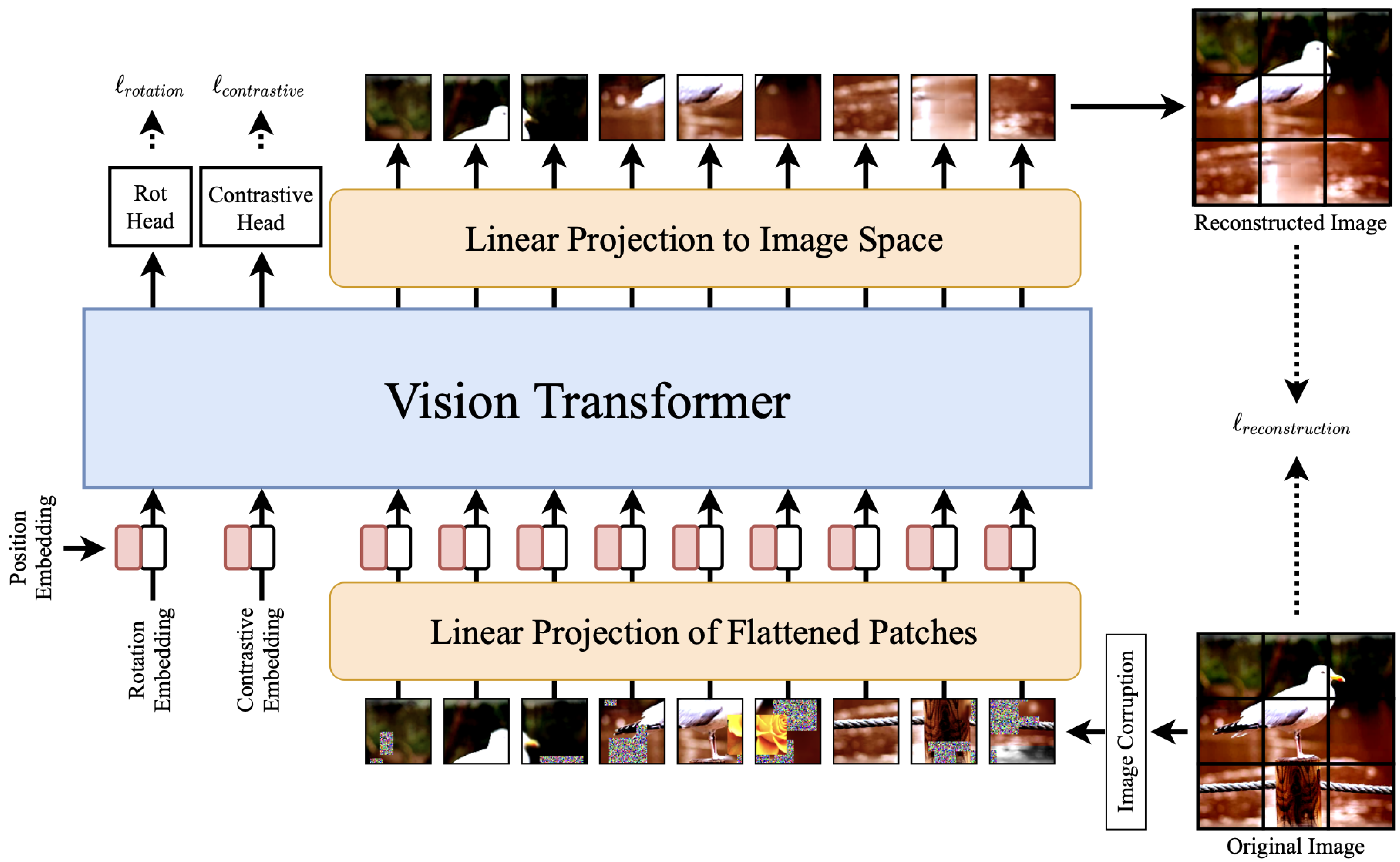


https://ai.googleblog.com/2020/12/transformers-for-image-recognition-at.html

2 - Self-supervised Vision Transformer

Self-supervised Vision Transformer (SiT)

- ViT only works on big supervised datasets (ImageNet). Can we benefit from self-supervised learning as in BERT or GPT?
- The Self-supervised Vision Transformer (SiT) has an denoising autoencoder-like structure, reconstructing corrupted patches autoregressively.



Atito, S., Awais, M., and Kittler, J. (2021). SiT: Self-supervised vIsion Transformer. arXiv:2104.03602

Self-supervised Vision Transformer (SiT)

- Self-supervised learning is possible through from **data augmentation**, where various corruptions (masking, replacing, color distortion, blurring) are applied to the input image, but SiT must reconstruct the original image (denoising autoencoder, **reconstruction loss**).

- An auxiliary **rotation loss** forces SiT to predict the orientation of the image (e.g. 30°).
- An auxiliary **contrastive loss** ensures that high-level representations are different for different images.

Method	Backbone	Linear Evaluation			Domain Transfer	
		CIFAR10	CIFAR100	Tiny-ImageNet	C100→C10	C10 →C100
DeepCluster [19]	ResNet-32	$43.31\% \pm 0.62$	$20.44\% \pm 0.80$	$11.64\% \pm 0.21$	$43.39\% \pm 1.84$	$18.37\% \pm 0.41$
RotationNet [23]	ResNet-32	$62.00\% \pm 0.79$	$29.02\% \pm 0.18$	$14.73\% \pm 0.48$	$52.22\% \pm 0.70$	$27.02\% \pm 0.20$
Deep InfoMax [20]	ResNet-32	$47.13\% \pm 0.45$	$24.07\% \pm 0.05$	$17.51\% \pm 0.15$	$45.05\% \pm 0.24$	$23.73\% \pm 0.04$
SimCLR [8]	ResNet-32	$77.02\% \pm 0.64$	$42.13\% \pm 0.35$	$25.79\% \pm 0.4$	$65.59\% \pm 0.76$	$36.21\% \pm 0.16$
SimCLR [8]	ResNet-56	$78.75\% \pm 0.24$	$44.33\% \pm 0.48$	n/a	$66.19\% \pm 0.80$	$36.79\% \pm 0.45$
Relational Reasoning [21]	ResNet-32	$74.99\% \pm 0.07$	$46.17\% \pm 0.16$	$30.54\% \pm 0.42$	$67.81\% \pm 0.42$	$41.50\% \pm 0.35$
Relational Reasoning [21]	ResNet-56	$77.51\% \pm 0.00$	$47.90\% \pm 0.27$	n/a	$68.66\% \pm 0.21$	$42.19\% \pm 0.28$
SiT (ours) - Linear projection	Transformer	$81.98\% \pm 0.24$	$54.31\% \pm 0.13$	$40.35\% \pm 0.27$	$73.79\% \pm 0.15$	$55.72\% \pm 0.13$
SiT (ours) - Non-Linear projection	Transformer	$\mathbf{83.50}\% \pm 0.11$	$\mathbf{57.75}\% \pm 0.21$	$\mathbf{43.06}\% \pm 0.14$	$\mathbf{75.52}\% \pm 0.11$	$\mathbf{57.89}\% \pm 0.14$

Self-distillation with no labels (DINO)

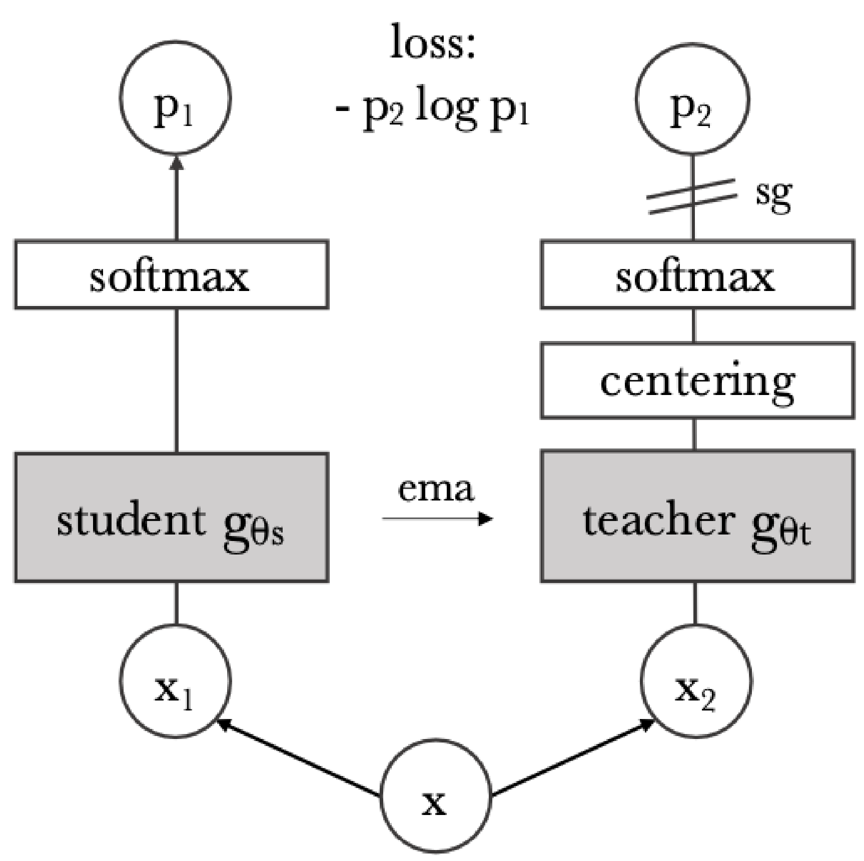
- Another approach for self-supervised learning has been proposed by Facebook AI using **self-distillation**.
- The images are split into **global** and **local patches** at different scales.
- Global patches contain label-related information (whole objects) while local patches contain finer details.

Davide Coccomini | 2021

Source: https://towardsdatascience.com/on-dino-self-distillation-with-no-labels-c29e9365e382

Self-distillation with no labels (DINO)

- The idea of **self-distillation** in DINO is to use two similar ViT networks to classify the patches.
- The **teacher** network gets the global views as an input, while the **student** network get both the local and global ones.
- Both have a MLP head to predict the softmax probabilities, but do **not** use any labels.



- The student tries to imitate the output of the teacher, by minimizing the **cross-entropy** (or KL divergence) between the two probability distributions.
- The teacher slowly integrates the weights of the student (momentum or exponentially moving average ema):

$$\theta_{\text{teacher}} \leftarrow \beta \, \theta_{\text{teacher}} + (1 - \beta) \, \theta_{\text{student}}$$

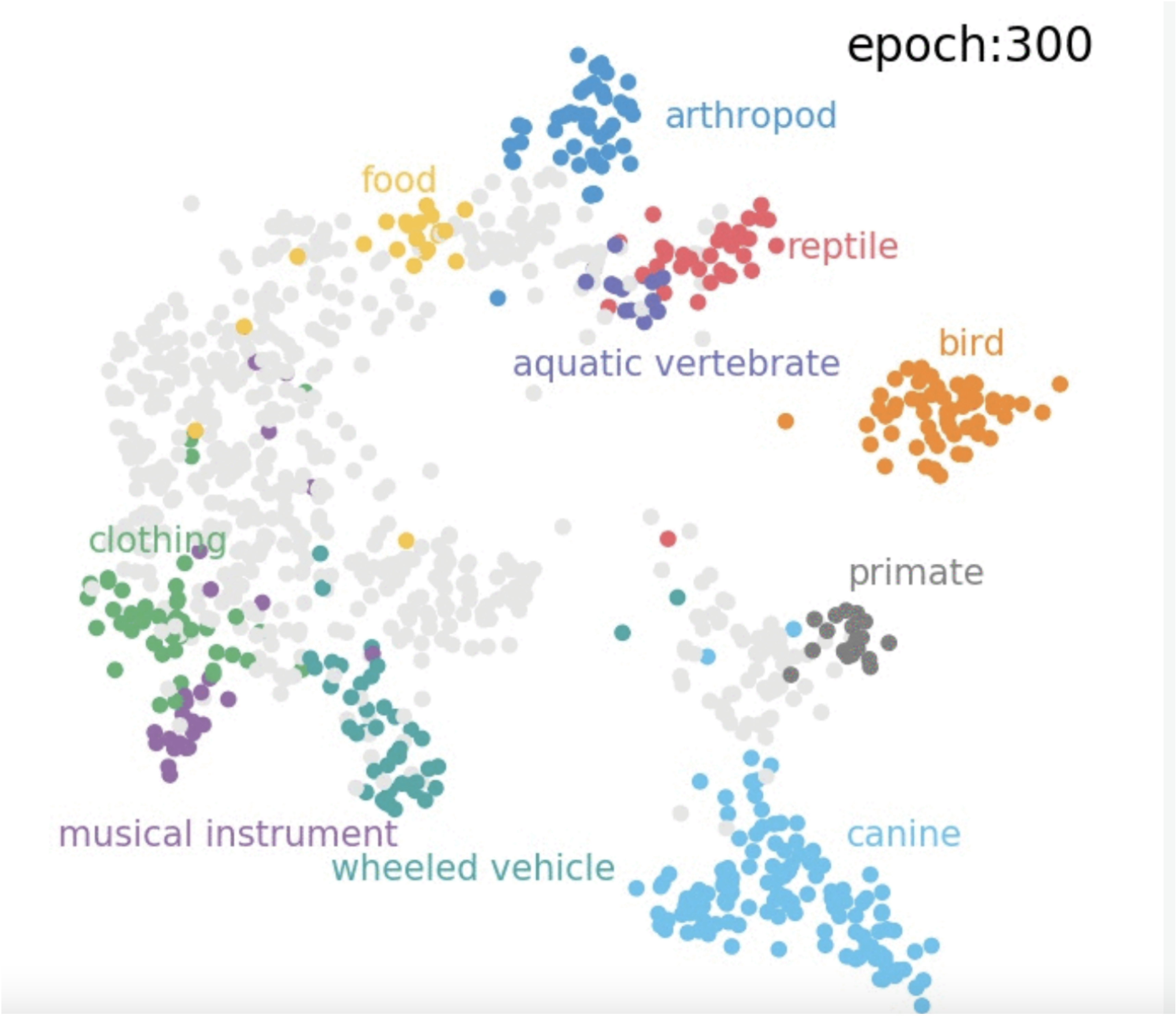
Self-distillation with no labels (DINO)

Source: https://ai.facebook.com/blog/dino-paws-computer-vision-with-self-supervised-transformers-and-10x-more-efficient-training/

Caron, M., Touvron, H., Misra, I., Jégou, H., Mairal, J., Bojanowski, P., et al. (2021). Emerging Properties in Self-Supervised Vision Transformers. arXiv:2104.14294

Self-distillation with no labels (DINO)

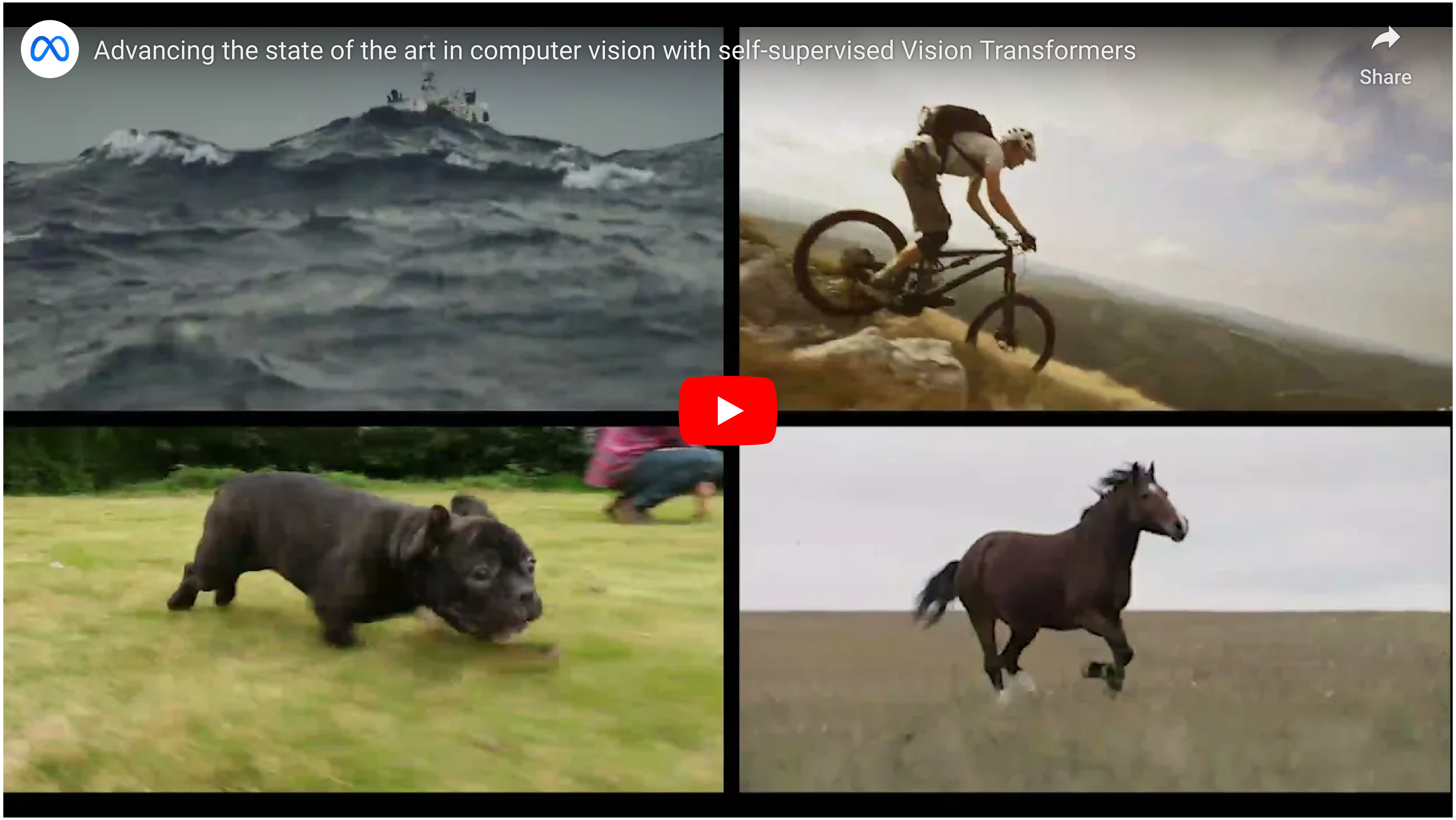
- The predicted classes do not matter when pre-training, as there is no ground truth.
- The only thing that matters is the **high-level representation** of an image before the softmax output, which can be used for transfer learning.
- Self-distillation forces the representations to be meaningful at both the global and local scales, as the teacher gets global views.
- ImageNet classes are already separated in the high-level representations: a simple kNN (k-nearest neighbour) classifier achieves 74.5% accuracy (vs. 79.3% for a supervised ResNet50).



https://ai.facebook.com/blog/dino-paws-computer-vision-with-self-supervised-transformers-and-10x-more-efficient-training

Self-distillation with no labels (DINO)

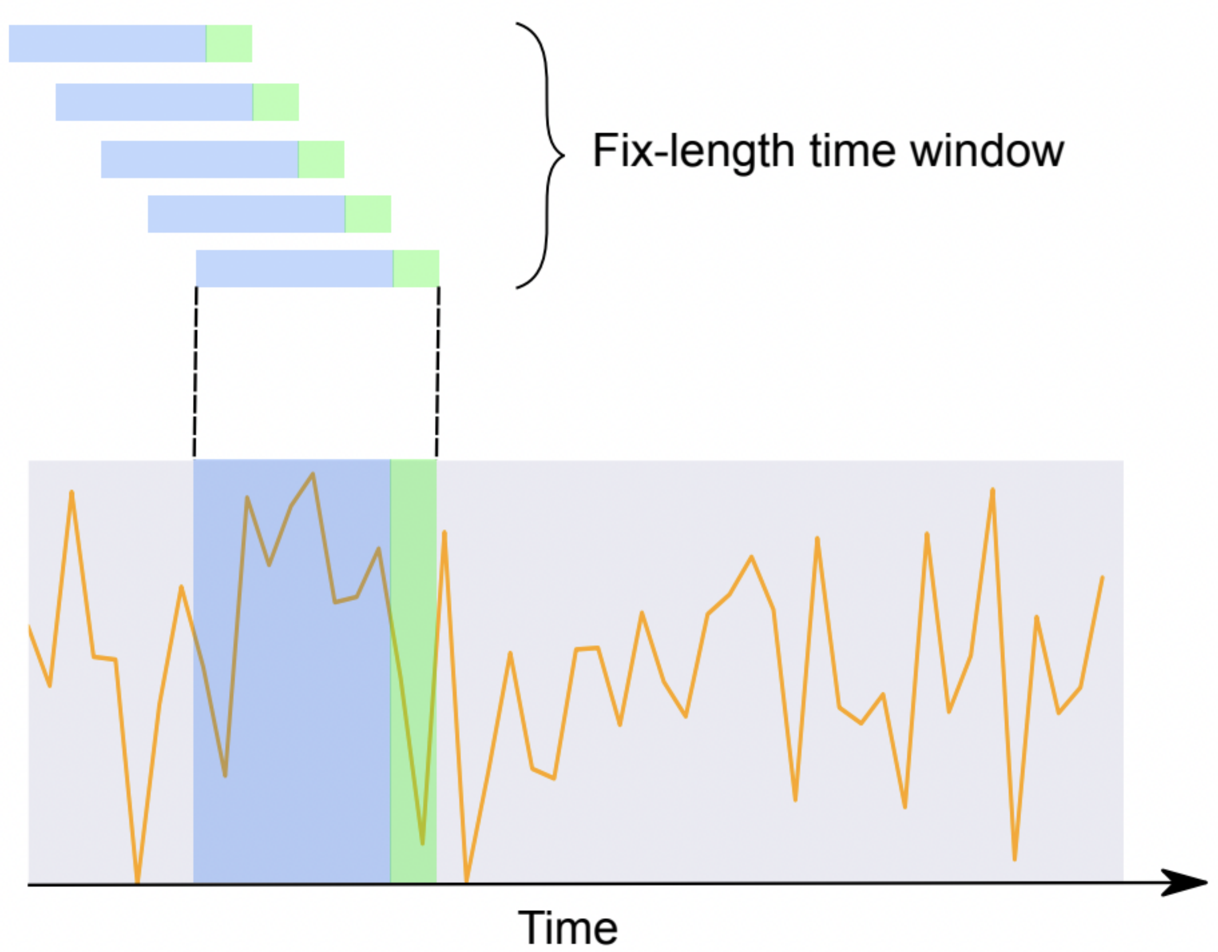
- More interestingly, by looking at the self-attention layers, one can obtain saliency maps that perform **object segmentation** without ever having been trained to!

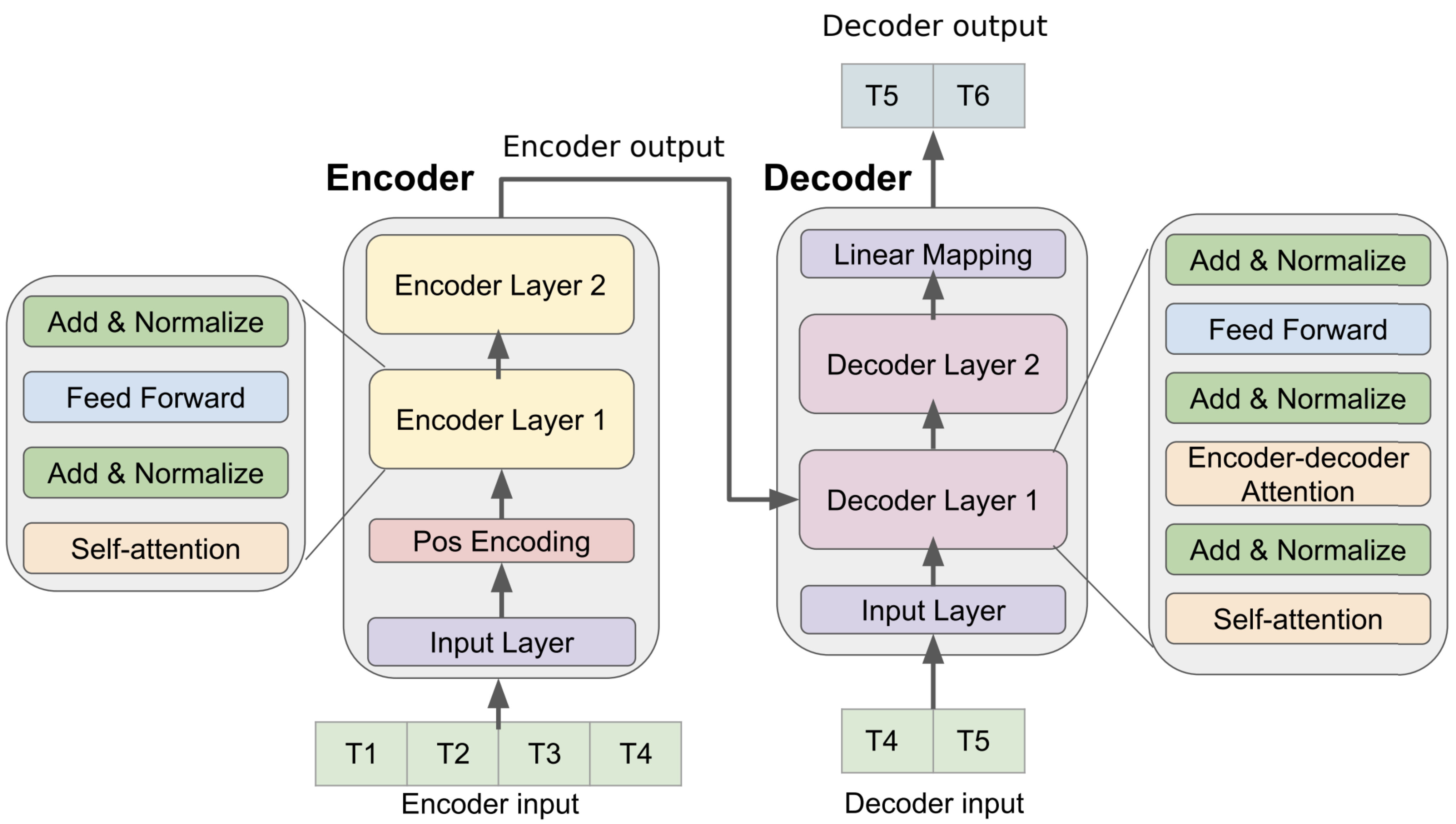


3 - Other domains

Transformer for time series

- Transformers can also be used for time-series classification or forecasting instead of RNNs.
- Example: weather forecasting, market prices, etc.

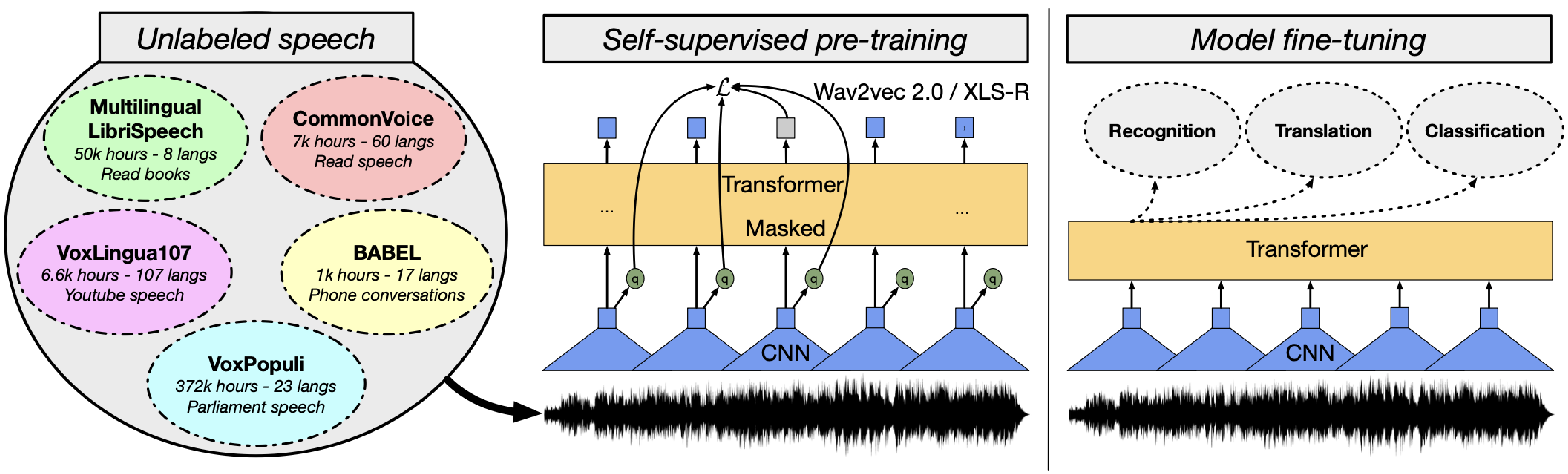




Wu, N., Green, B., Ben, X., and O'Banion, S. (2020). Deep Transformer Models for Time Series Forecasting: The Influenza Prevalence Case. arXiv:2001.08317

Speech processing

- XLS-R from Facebook is a transformer-based architecture trained on 436,000 hours of publicly available speech recordings, from 128 languages.
- Self-supervised: contrastive learning and masked language modelling.
- Other models: UniSpeech, HuBERT, BigSSL…



Source: https://ai.facebook.com/blog/xls-r-self-supervised-speech-processing-for-128-languages/

Additional resources

https://theaisummer.com/vision-transformer/

https://theaisummer.com/transformers-computer-vision/

https://iaml-it.github.io/posts/2021-04-28-transformers-in-vision/

https://d2l.ai/chapter_attention-mechanisms-and-transformers/vision-transformer.html