

# Machine Learning for Computer Vision

# TD3: Vision Transformer (ViT) and object detection

# Département d'informatique

#### Ruiwen HE

# Course Review: Vision Transformer (ViT) and object detection

# Vision Transformer (ViT)

### Overview

- Adaptation of the Transformer architecture, originally designed for NLP, to computer vision tasks.
- Divides an image into patches and processes them as a sequence of tokens.

## **Key Concepts**

- Patch Embeddings: Images are split into fixed-size patches (e.g., 16 × 16) and flattened to form patch embeddings.
- Self-Attention Mechanism: Models global dependencies across all patches, enabling better understanding of spatial relationships.
- Positional Encoding: Maintains spatial information within the patches.

# Strengths

- Excellent at learning global features compared to CNNs, which focus on local features.
- Scalable with large datasets (e.g., ImageNet-21k).

#### Limitations

- Requires a large amount of data for effective training.
- Computationally expensive compared to traditional CNNs.

## **Applications**

■ Image classification, segmentation, and other computer vision tasks.

# **Object Detection**

## **Definition**

 Identifying and localizing objects within an image, typically by generating bounding boxes and classifying objects.

## Popular Models

- YOLO (You Only Look Once):
  - Real-time object detection.
  - Divides images into grids and predicts bounding boxes and class probabilities in one pass.

#### ■ DETR (DEtection TRansformer):

- Combines transformer-based attention mechanisms with object detection.
- Processes images as a sequence, eliminating the need for anchor boxes.

## Comparison Between YOLO and DETR

#### • YOLO:

- Faster inference.
- Suited for real-time applications.
- Anchor-based detection with predefined sizes.

### • DETR:

- Better at modeling complex spatial relationships.
- Requires more training time but removes the need for anchors.

# **Applications**

• Autonomous vehicles, surveillance, medical imaging, and retail analytics.

## **Takeaways**

- ViT and DETR are examples of how transformer-based architectures are reshaping vision tasks, providing flexibility and global context understanding.
- YOLO remains a robust choice for speed-critical applications.
- A combination of methods (e.g., ViT for classification, YOLO/DETR for detection) can cater to diverse real-world needs.

# Part I: Basics of Image Segmentation and Evaluation Metrics

### Introduction

This practical session is divided into three exercises focusing on model comparisons, training object detection models, and evaluating their performance on video data.

### Exercise 1: Comparison of ViT and Traditional CNN Models

■ **Objective:** Analyze the performance of Vision Transformer (ViT) and traditional CNN models for classification tasks.

### Tasks:

- 1. Train ViT and CNN models on a specific dataset.
- 2. Evaluate their classification performance using metrics such as accuracy, recall, and F1-score.
- 3. Compare results obtained with pre-trained models versus models trained from scratch.

### Exercise 2: Training and Testing YOLOv5

■ Objective: Train the YOLOv5 model on a custom dataset and evaluate its performance on video data.

#### ■ Tasks:

- 1. Configure the YOLOv5 model using a dataset obtained via the https://public.roboflow.comRoboflow API.
- 2. Adjust model parameters (e.g., number of classes, train/validation split) and train the model.
- 3. Validate the model on video data and generate a video showcasing its predictions.

# Exercise 3: Training and Testing DETR

- Objective: Train and evaluate the DETR (DEtection TRansformer) model on a similar dataset.
- Tasks:
  - 1. Train the DETR model on a dataset comparable to the one used for YOLOv5.
  - 2. Test the trained DETR model on video data.
  - 3. Generate a video illustrating the model's predictions.

# **Bonus Opportunity**

If you submit the final test video with the predicted results back to us, additional bonus points will be awarded. This will ensure models are evaluated on a unified dataset, offering a clearer demonstration of their practical effectiveness.