Computer Vision – 2025

Lecture #05. Segmentation and Object Detection

Lectures by Alexei Kornaev [1,2,3]
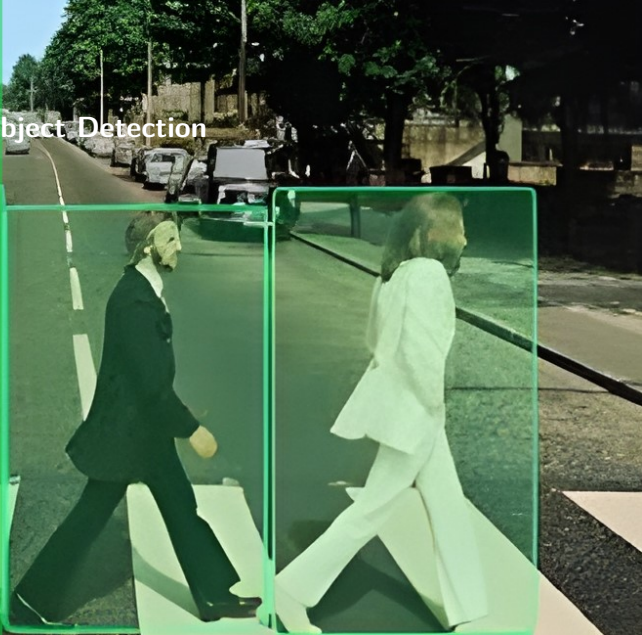Practical sessions by Kirill Yakovlev [2]

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Agenda

1 Outcomes

2 Introduction

3 U-Net: Semantic Segmentation

4 Segment Anything Model (SAM)

5 Conclusion

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Section 1. Outcomes

Outcomes

This week's lecture and seminar on Segmentation and Object Detection aims to provide an understanding of deep learning-based segmentation methods and object detection techniques. By the end of this week, students will be able to:

1. Understand semantic segmentation and object detection concepts.
2. Describe models such as U-Net, DeepLab, Mask R-CNN, YOLO, Faster R-CNN, and SAM.
3. Implement segmentation models using PyTorch or TensorFlow.

Key Takeaway: Deep learning-based segmentation and object detection methods enable precise image analysis for various applications, from medical imaging to autonomous driving.

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Section 2. Introduction

Types of Image Segmentation
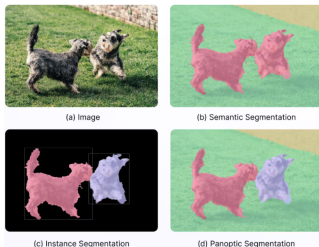
Segmentation Overview

Image segmentation is the process of partitioning an image into meaningful regions. It plays a key role in medical imaging, autonomous driving, and scene understanding.

- **Semantic Segmentation:** Classifies each pixel into predefined object categories.
- **Instance Segmentation:** Identifies individual object instances within categories.
- **Panoptic Segmentation:** Unifies semantic and instance segmentation by labeling both things (objects) and stuff (background regions).

(a) Image   (b) Semantic Segmentation

(c) Instance Segmentation   (d) Panoptic Segmentation

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Figure: Types of segmentation problems.

Principles of Semantic Segmentation

Key Idea

Semantic segmentation assigns a class label to each pixel without distinguishing between object instances.

- Uses fully convolutional networks (FCNs) to generate dense predictions.
- Common architectures: U-Net [Ronneberger et al., 2015], DeepLab [Chen et al., 2018].
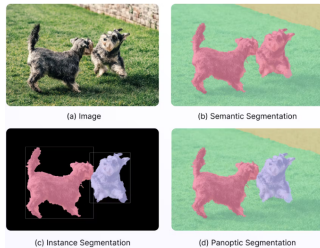- Loss functions: Cross-entropy loss, Dice loss, IoU loss.

(a) Image

(b) Semantic Segmentation

(c) Instance Segmentation

(d) Panoptic Segmentation

Figure: Types of segmentation problems.

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Principles of Instance Segmentation

Key Idea

Instance segmentation detects and segments each object instance separately, unlike semantic segmentation.

- Combines object detection and segmentation.
- Example models: Mask R-CNN [He et al., 2018], SOLOv2 [Wang et al., 2020].
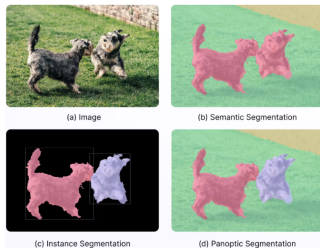- Applications: Robotics, medical imaging, autonomous driving.

(a) Image
(b) Semantic Segmentation
(c) Instance Segmentation
(d) Panoptic Segmentation

Figure: Types of segmentation problems.

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Principles of Panoptic Segmentation
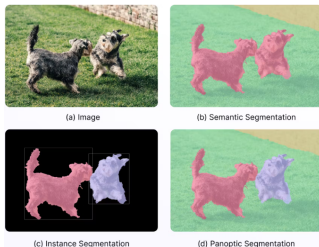
Key Idea

Panoptic segmentation unifies semantic and instance segmentation by labeling both objects and background regions.

- Combines "stuff" segmentation (background regions) with "thing" segmentation (object instances).
- Example models: Panoptic FPN [Kirillov et al., 2019], DETR [Carion et al., 2020].
- Applied in urban scene understanding, AR/VR, and satellite imagery.

(a) Image (b) Semantic Segmentation

(c) Instance Segmentation (d) Panoptic Segmentation

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Figure: Types of segmentation problems.

Comparison of Segmentation Types

- **Semantic Segmentation:** Classifies each pixel but does not differentiate object instances.
- **Instance Segmentation:** Separates individual objects within a category.
- **Panoptic Segmentation:** Merges both approaches, distinguishing objects and background.

Aspect	Semantic	Instance	Panoptic
Pixel-wise classification	Yes	Yes	Yes
Object instance distinction	No	Yes	Yes
Stuff vs. things distinction	No	No	Yes
Example models	U-Net, DeepLab	Mask R-CNN, SOLO	Panoptic FPN, DETR

Table: Comparison of segmentation approaches.

Principles of Object Detection

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Key Idea

Object detection identifies and localizes objects in an image by predicting bounding boxes and class labels.

- Combines classification and localization to detect multiple objects.
- Two-stage detectors: Region proposal + classification (e.g., Faster R-CNN [Ren et al., 2016]).
- One-stage detectors: Direct prediction (e.g., YOLO [Redmon et al., 2016]).
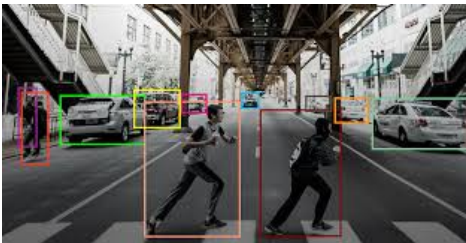- Applications: Autonomous vehicles, surveillance, medical imaging.

Figure: Example of object detection.

Section 3. U-Net: Semantic Segmentation

Key Ideas of U-Net

Key Idea

U-Net is a fully convolutional neural network designed for biomedical image segmentation. It follows a U-shaped architecture with an encoder-decoder structure.

- Encoder: Uses convolutional and pooling layers to extract feature maps.
- Bottleneck: Captures deep features with high-level abstractions.
- Decoder: Uses upsampling and skip connections to reconstruct segmentation masks.
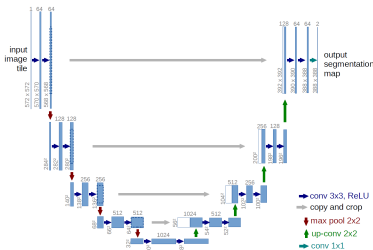

Figure: U-Net architecture [Ronneberger et al., 2015].

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U-Net Architecture
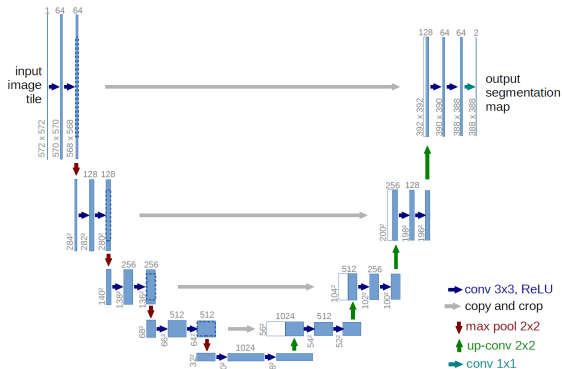
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- U-Net consists of a contracting path (encoder) and an expansive path (decoder).
- Skip connections concatenate corresponding encoder and decoder feature maps to retain spatial details.
- Final layer applies a 1x1 convolution to obtain pixel-wise classification.

Figure: Detailed U-Net structure [Ronneberger et al., 2015].

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Residual Connections in U-Net

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Key Idea (He et al., 2015)

Residual connections help mitigate the vanishing gradient problem and improve gradient flow in deep networks.

- A residual connection allows the gradient to bypass some layers, making training easier.
- Instead of learning the full transformation $F(x)$, the network learns the residual function $F(x) + x$.
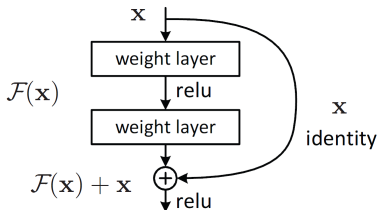- Some U-Net variants, such as ResUNet, integrate residual blocks for better performance.

Figure: Residual connections in a CNN block.

Upsampling in U-Net

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- U-Net uses upsampling to restore spatial resolution in the decoder.
- Two main types of upsampling:
  - **Interpolation-based Upsampling:** Bilinear or nearest neighbor interpolation followed by convolution.
  - **Transposed Convolution (Deconvolution):** Learnable filters upscale feature maps.
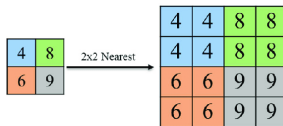

Figure: Nearest neighbor interpolation [Prince, 2023].

Transposed Convolution (Deconvolution)

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- Transposed convolution is a learnable upsampling method.
- Instead of direct interpolation, it applies convolution on an expanded input.
- Steps:
  1. Insert zeros between pixels (if stride > 1).
  2. Convolve with a learnable kernel.
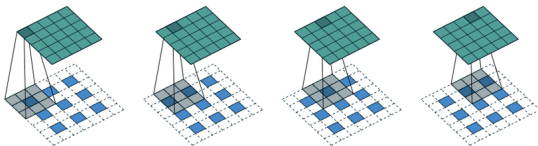 3. Output has a larger spatial resolution.

Figure: Example of transposed convolution operation.

Loss Functions for U-Net

- **Cross-Entropy Loss:** Pixel-wise loss for multi-class segmentation.

$$\mathcal{L}_{CE} = -\frac{1}{m \cdot H \cdot W} \sum_{i=1}^{m} \sum_{x=1}^{H} \sum_{y=1}^{W} \sum_{k=1}^{N} y_k^{(i)}(x, y) \log(h_k^{(i)}(x, y)) \qquad (1)$$

- **Dice Loss:** Optimized for imbalanced datasets.

$$\mathcal{L}_{Dice} = 1 - \frac{2 \sum_{i=1}^{m} \sum_{x=1}^{H} \sum_{y=1}^{W} \sum_{k=1}^{N} y_k^{(i)}(x, y) h_k^{(i)}(x, y)}{\sum_{i=1}^{m} \sum_{x=1}^{H} \sum_{y=1}^{W} \sum_{k=1}^{N} y_k^{(i)}(x, y) + \sum_{i=1}^{m} \sum_{x=1}^{H} \sum_{y=1}^{W} \sum_{k=1}^{N} h_k^{(i)}(x, y)} \qquad (2)$$

- **IoU Loss:** Measures the intersection-over-union between prediction and ground truth.

$$\mathcal{L}_{IoU} = 1 - \frac{\sum_{i=1}^{m} \sum_{x=1}^{H} \sum_{y=1}^{W} \sum_{k=1}^{N} y_k^{(i)}(x, y) h_k^{(i)}(x, y)}{\sum_{i=1}^{m} \sum_{x=1}^{H} \sum_{y=1}^{W} \sum_{k=1}^{N} \left(y_k^{(i)}(x, y) + h_k^{(i)}(x, y) - y_k^{(i)}(x, y) h_k^{(i)}(x, y) \right)} \qquad (3)$$

where m is the number of images of size $H \times W$, N is the number of classes, $y_k^{(i)}(x, y)$ is the label for pixel (x, y) in image i (one-hot encoded), $h_k^{(i)}(x, y)$ is the prediction.

Metrics for U-Net Evaluation

- **Dice Coefficient:** Measures segmentation accuracy.
- **Intersection over Union (IoU):** Evaluates overlap between prediction and ground truth.
- **Pixel Accuracy:** Computes correctly classified pixels.
- **Mean IoU:** Averages IoU across all classes.

$$\text{IoU} = \frac{|\mathbf{y} \cap \mathbf{h}|}{|\mathbf{y} \cup \mathbf{h}|} \tag{4}$$

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Applications of U-Net

- **Medical Imaging:** Segmentation of tumors, organs, and tissues.
- **Satellite Image Analysis:** Land cover classification and urban planning.
- **Autonomous Driving:** Road scene understanding.
- **Agriculture:** Crop and plant segmentation from aerial images.

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Section 4. Segment Anything Model (SAM)

What is SAM?

Key Idea

The Segment Anything Model (SAM) is a foundation model for segmentation developed by Meta AI. It can segment any object in an image using different input prompts, making it highly versatile.

- Works with bounding boxes, clicks, or freeform masks as prompts.
- Trained on SA-1B dataset with over 1 billion masks.
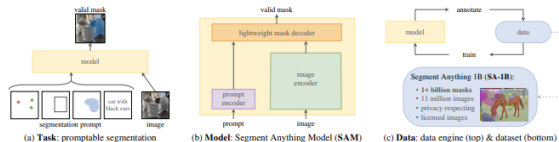- Enables zero-shot segmentation on unseen images.

Figure: SAM Model Overview.

SAM Architecture

- **Image Encoder:** A large Vision Transformer (ViT) pre-trained using masked autoencoding.
- **Prompt Encoder:** Processes input prompts (points, boxes, masks).
- **Mask Decoder:** Predicts segmentation masks based on encoded image and prompts.
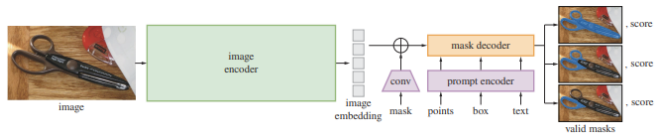

Figure: Segment Anything Model (SAM) Architecture.

Training and Dataset

- **SA-1B Dataset:** The largest segmentation dataset with 1 billion masks.
- **Semi-Automatic Annotation:** Human annotators refined AI-generated masks.
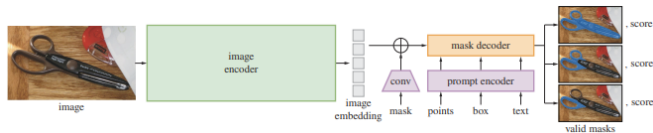- **Generalization:** Trained to segment unseen objects and domains.

Figure: Segment Anything Model (SAM) Architecture.

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How SAM Works?

- The user provides an input prompt (point, bounding box, or mask).
- SAM generates segmentation masks based on prompt and image encoding.
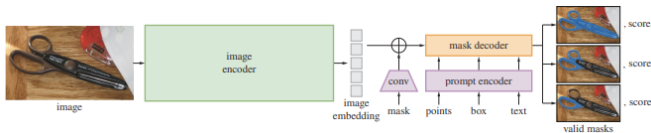- Output can be refined interactively.

Figure: Segment Anything Model (SAM) Architecture.

Applications of SAM

- **Medical Imaging:** Tumor and organ segmentation.
- **Autonomous Driving:** Road scene segmentation.
- **AR/VR:** Object segmentation for augmented reality.
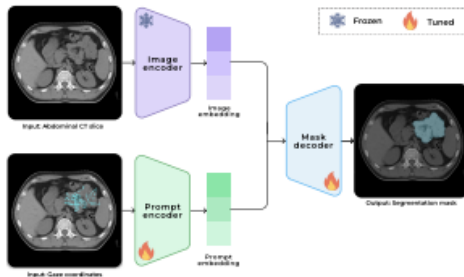- **Robotics:** Object recognition and manipulation.

Figure: Medical Application of SAM.

Key Takeaways

- SAM is a powerful, zero-shot segmentation model.
- Works with multiple input prompts for flexible segmentation.
- Trained on the largest segmentation dataset, enabling generalization.
- Open-source and widely applicable across industries.

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Section 5. Conclusion

Key Takeaways

- Segmentation and detection are essential for computer vision applications.
- Deep learning-based models have achieved state-of-the-art performance.
- Practical implementation involves dataset preparation, model training, and evaluation.

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