Practices in visual computing 1

Lab11: Fine-Tuning SAM2 and Detectron2

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Outline

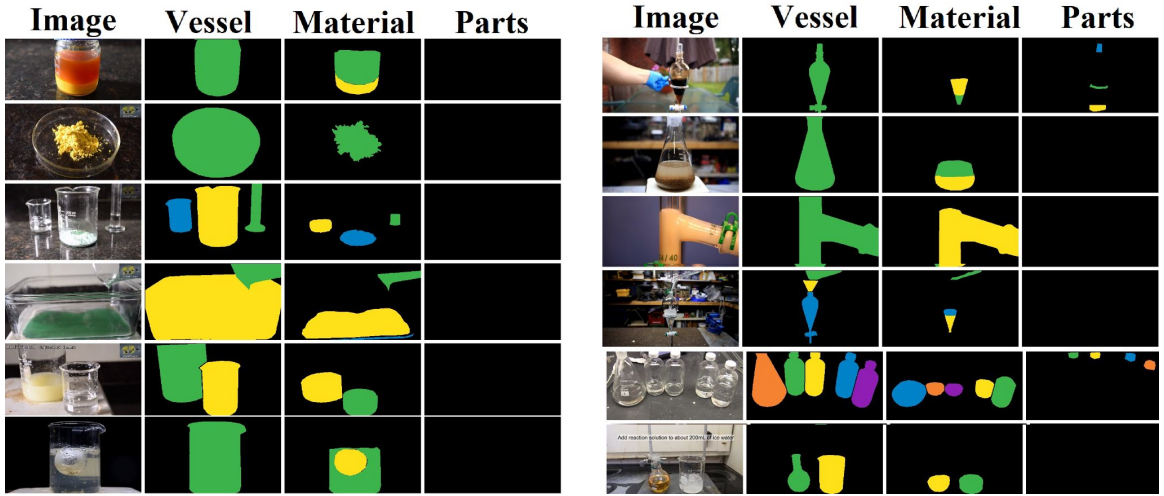
- SAM2 Fine-Tuning
- Mixed Precision Training
- Detectron2 Overview
- Fine-Tuning Detectron2

LabPicsV1 Dataset

A specialized dataset with annotated images of lab equipment, reagents, containers, and other lab objects.

Applications:

- Object detection and segmentation in laboratory settings
- Automated inventory management and safety monitoring



SAM2 Fine-Tuning

Steps:

- Prepare Data
  - Load LabPicsV1 in proper foramt
- Model Configuration
  - Load pre-trained SAM2 weights.
  - Adjust model layers if necessary (e.g., task-specific heads).
- Fine-Tuning

Optimizer: AdamW - Learning Rate: 1e-5 - Weight Decay: 4e-5

Mixed Precision Training

Combines FP16 and FP32 for faster computation and reduced memory usage.

Benefits:

- Faster training
- Lower GPU memory usage
- Maintains model accuracy using dynamic scaling

Key PyTorch tools:

- torch.cuda.amp
- GradScaler

Float16 vs Float32

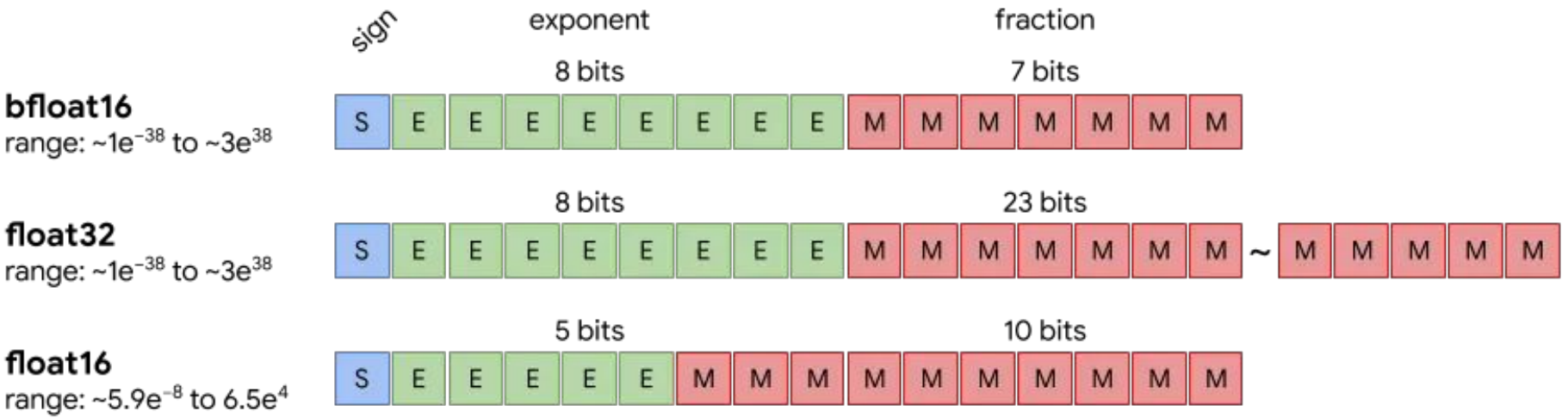
FP16 (Half-Precision):

- 16 bits per number, lower memory usage
- Faster computation on compatible GPUs
- Limited range and precision, prone to overflow/underflow

FP32 (Single-Precision):

- 32 bits per number, higher memory usage
- Stable gradients and wider precision range
- Slower computation compared to FP16

Float16 vs Float32



What is Mixed Precision?

Uses multiple numerical precision levels (e.g., FP32, FP16, BF16).

Balances computational efficiency and accuracy.

Benefits:

- Faster Computation: FP16/BF16 computations are faster.
- Reduced Memory Usage: FP16 uses half the memory of FP32.

Challenges of Mixed Precision

Numerical Instability:

- FP16 struggles with very small or very large values, leading to underflow or overflow.

Implementation Complexity:

- Managing precision requires careful handling.

Challenges of Mixed Precision

When to Use FP16:

- Matrix multiplications and other operations with large intermediate results.
- Suitable for most neural network layers to speed up computations.

When to Use FP32:

- Critical operations like loss calculations and gradient updates.
- Ensures numerical stability for small or sensitive values.

torch.cuda.amp

Automates mixed precision (AMP) training

- torch.cuda.amp.autocast(): Chooses appropriate precision automatically
- GradScaler: Dynamically scales gradients to prevent underflow

Simplifies implementation

Improves performance and memory usage

GradScaler

Scales gradients during backpropagation

Checks for inf/nan values in gradients

Dynamically adjusts scaling factor

GradScaler.step(optimizer)

Performs the optimizer's parameter update step, potentially skipping updates if gradients contain non-finite values (e.g., NaN or Inf).

- GradScaler checks the scaled gradients for finiteness.
- If gradients are valid, it unscales them (divides by the scale factor) and passes them to the optimizer for the weight update.
- If gradients are not finite, the update step is skipped, avoiding unstable parameter updates.

GradScaler.update()

Adjusts the scale factor used for scaling gradients in the next iteration.

- If gradients were finite during the previous iteration, the scale factor may increase to enhance training efficiency.
- If gradients were non-finite, the scale factor is reduced to improve stability.
- This dynamic adjustment ensures that the model can maximize the precision benefits of FP16 while avoiding instability.

Detectron2

Detectron2 is an open-source framework, developed by Facebook AI Research is the improved successor to Detectron, offering a more flexible and user-friendly approach for developers and researchers.

Architecture of Detectron2

Backbone: Feature extractor (Feature Pyramid Network)

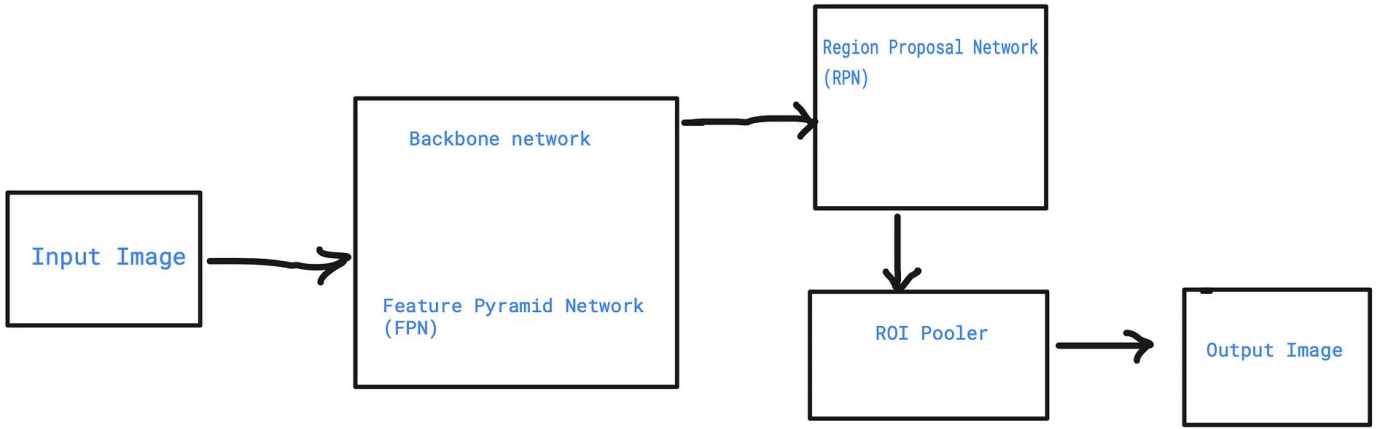
RPN (Region Proposal Network): Proposes candidate regions for detection.

Heads:

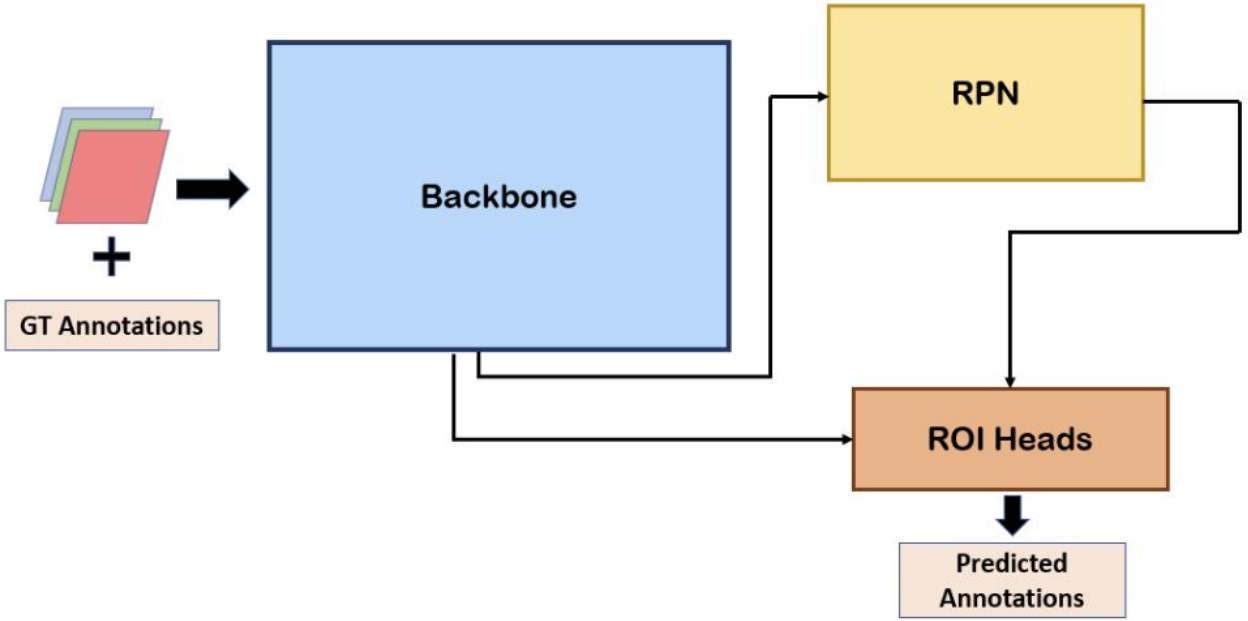
- Bounding Box Head: Refines region proposals into final detections.
- Mask Head: Predicts pixel-level masks for instances.
- Keypoint Head: Estimates keypoints for human pose estimation.

Loss Functions: Combines classification, regression, and segmentation losses.

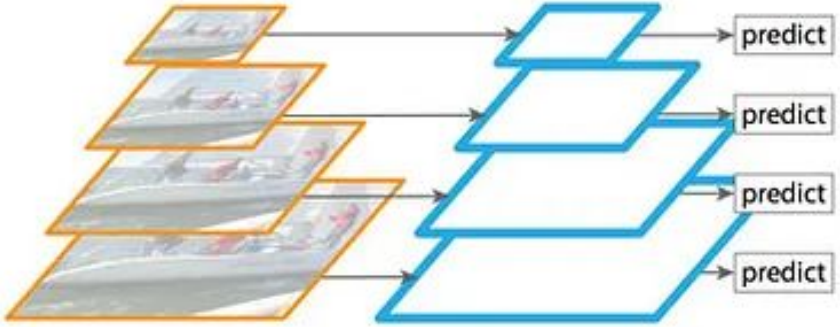
Architecture of Detectron2



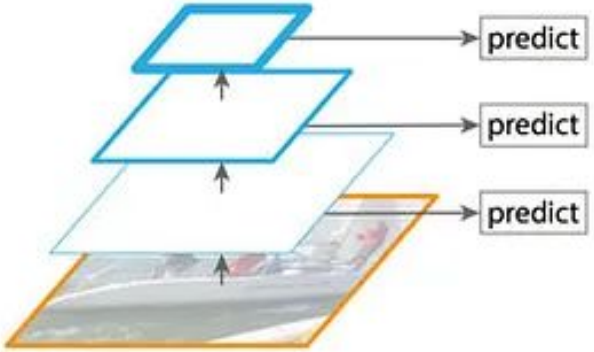
Architecture of Detectron2



Feature Pyramid Network



Pyramid of images

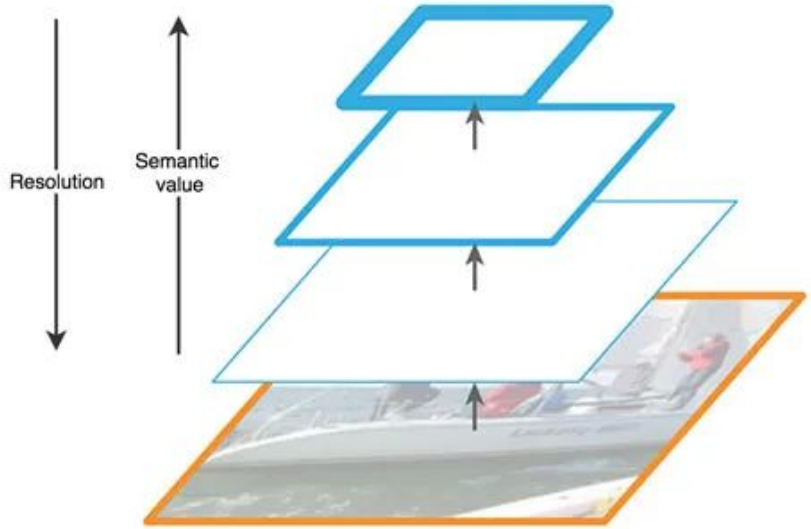


Pyramid of feature maps

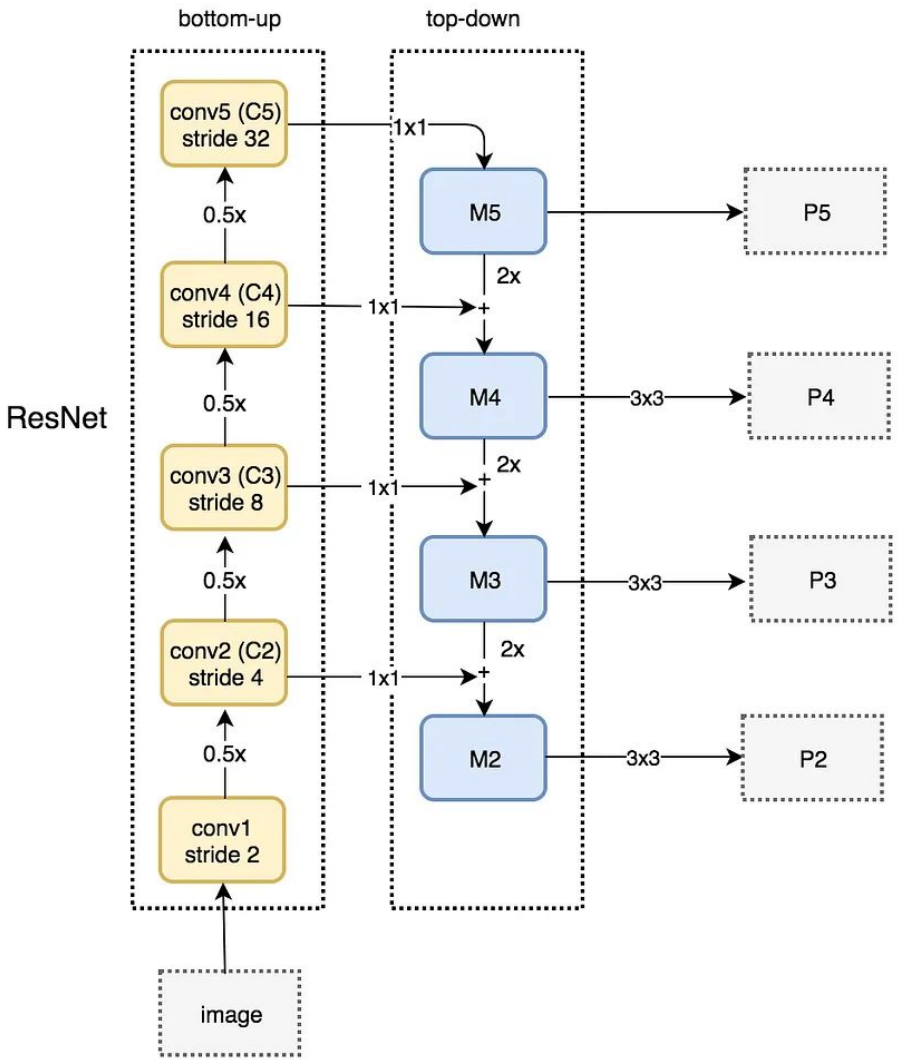
Bottom-up Pathway

Standard convolutional network for feature extraction.

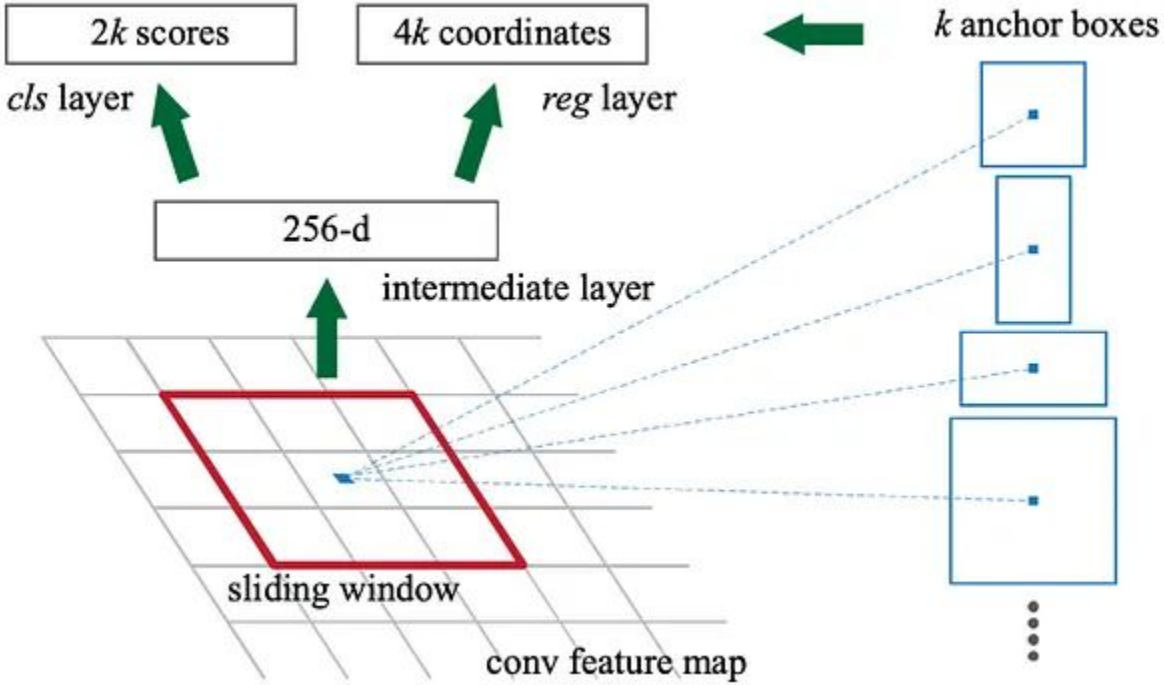
Processes input image to generate hierarchical feature maps.



Feature Pyramid Network



RPN (Region Proposal Network)



Detectron2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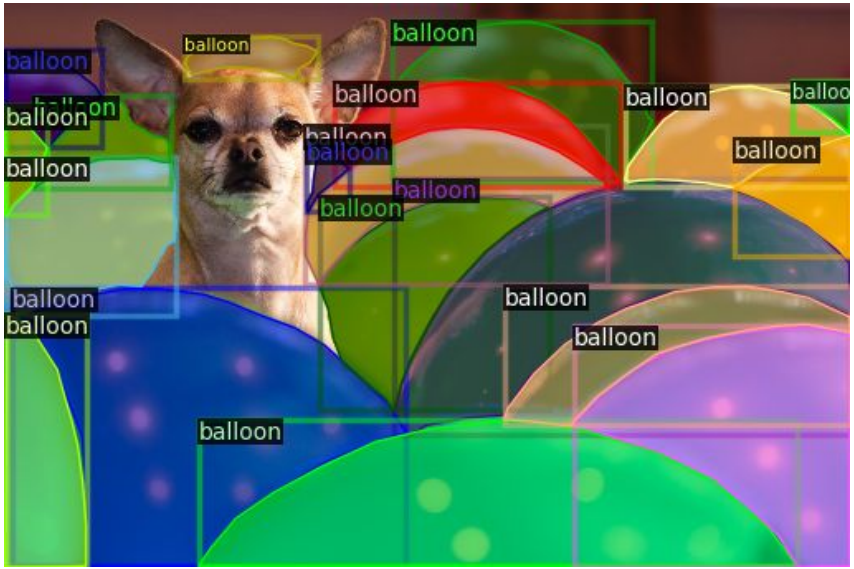
Fine-Tuning Detectron2 on Balloon Dataset

Train a Detectron2 model to detect and segment balloons in images.

Balloons are not included in Detectron2's pre-built datasets (e.g., COCO), so a custom dataset is required.



Fine-Tuning Detectron2 on Balloon Dataset

https://detectron2.readthedocs.io/en/latest/tutorials/datasets.html

https://detectron2.readthedocs.io/en/latest/modules/utils.html?highlight=visualizer#module-detectron2.utils.visualizer

https://detectron2.readthedocs.io/en/latest/modules/solver.html

Reference

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https://viso.ai/deep-learning/detectron2/

https://medium.com/@sumiteshn/a-gentle-introduction-to-detectron2-d5cb599cf001

Segment Anything, Kirillov et al - 2023