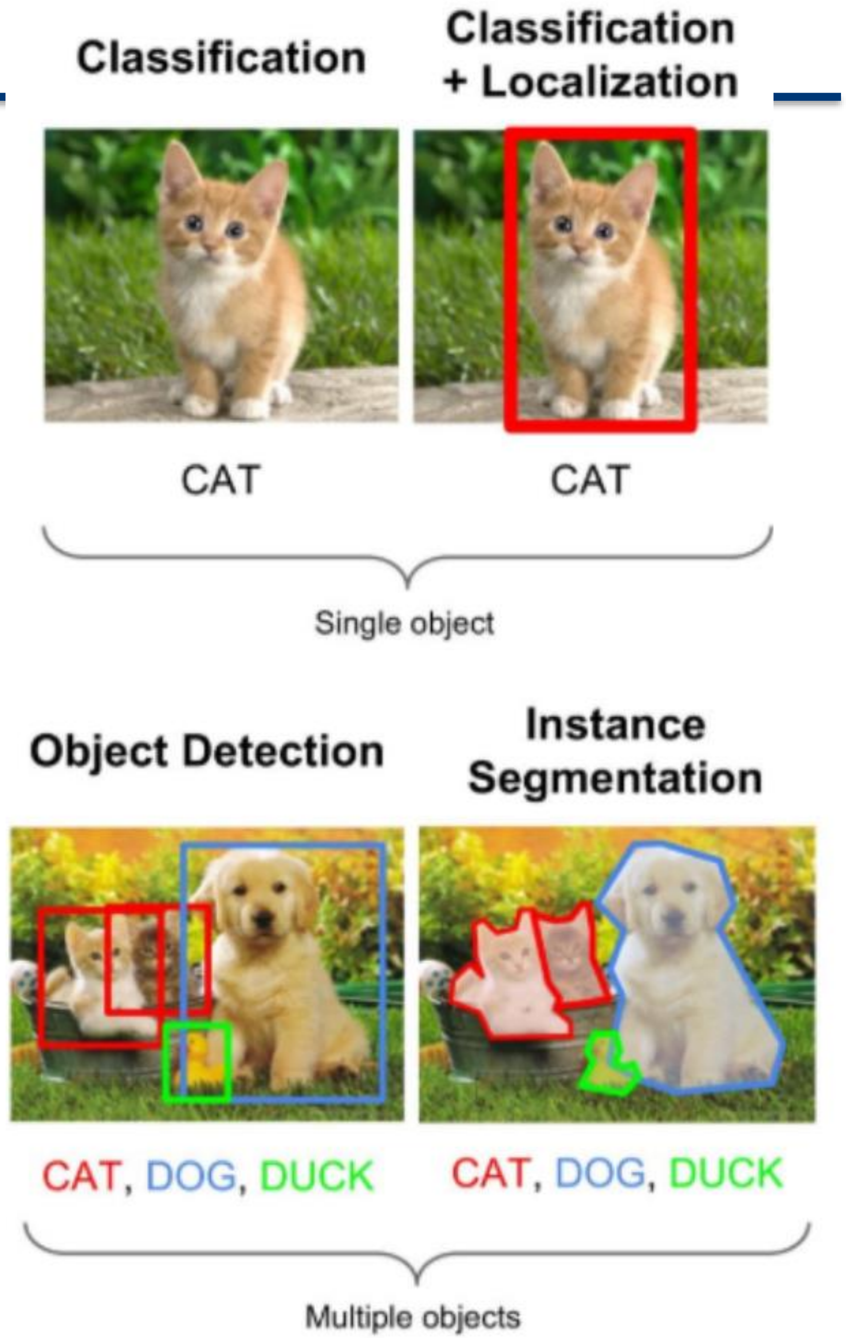
ComputerVision
Week7

2025-2

Mobile Systems Engineering
Dankook University

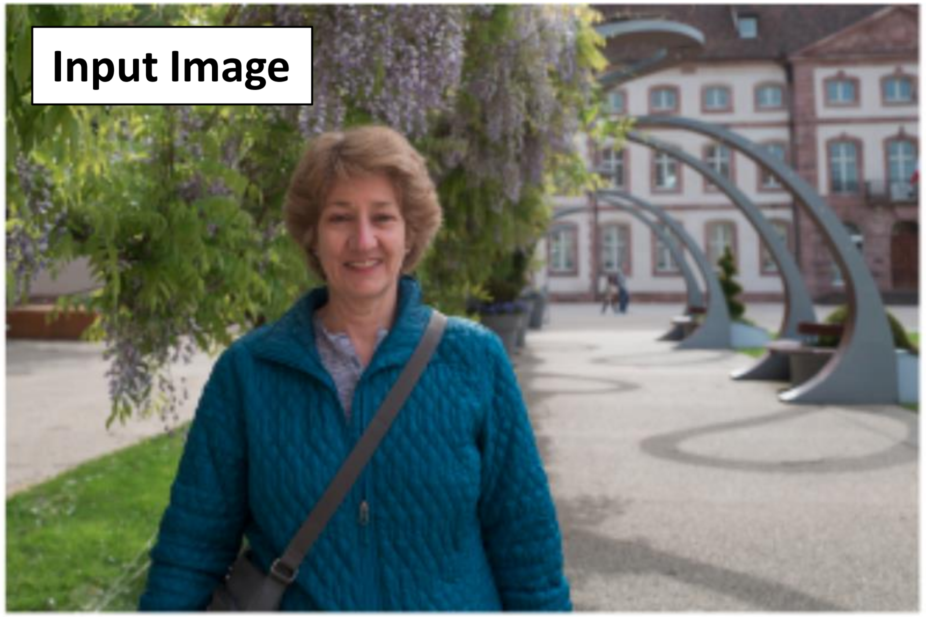
From Classification to Segmentation

- **Understanding different vision tasks**
  - **1. Classification – *Translation Invariance Task***
    - *"What is in the image?"*
    - Single label for the entire image.
  - **2. Classification + Localization – *Translation Variance Task***
    - *"What is it, and where is it?"*
    - Predicts class label and bounding box for **one object**.
  - **3. Object Detection – *Translation Variance Task***
    - *"What objects are there, and where are they?"*
    - Detects **multiple objects**, each with a bounding box and label.
  - **4. Instance Segmentation – *Translation Variance Task***
    - *"Which pixels belong to each object?"*
    - Pixel-level masks that separate even objects of the same class.



From Classification to Segmentation

- **Segmentation Types: Semantic vs. Instance**
  - **Segmentation Types in Computer Vision**
    - **1. Semantic Segmentation**



Segmented

Semantic Labels

3	3	3	3	3	3	3	3	3	3	3	3	5	5	5	5	5	5
3	3	3	3	3	3	3	3	3	3	3	3	5	5	5	5	5	5
3	3	3	3	3	3	1	1	3	3	3	3	5	5	5	5	5	5
3	3	3	3	3	1	1	1	1	3	3	3	5	5	5	5	5	5
3	3	3	3	3	3	1	1	3	3	3	5	5	5	5	5	5	5
5	5	3	3	3	3	1	1	3	3	5	5	5	5	5	5	5	5
4	4	3	4	1	1	1	1	1	1	4	4	4	5	5	5	5	5
4	4	3	4	1	1	1	1	1	1	4	4	4	4	4	5	5	5
4	4	4	1	1	1	1	1	1	1	1	4	4	4	4	4	4	4
3	3	3	1	1	1	1	1	1	1	1	4	4	4	4	4	4	4
3	3	3	1	2	2	1	1	1	1	1	4	4	4	4	4	4	4
3	3	3	1	2	2	1	1	1	1	1	4	4	4	4	4	4	4

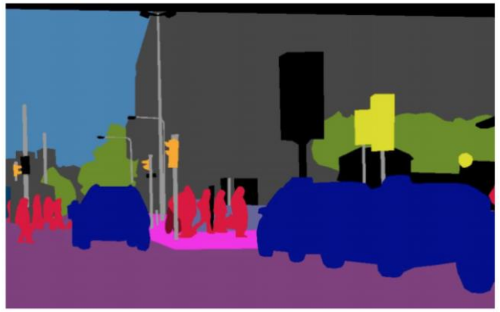
1: Person
2: Purse
3: Plants/Grass
4: Sidewalk
5: Building/Structures

✓Assigns a **class label to each pixel** in the image.

✓All objects of the same class share the **same label**.

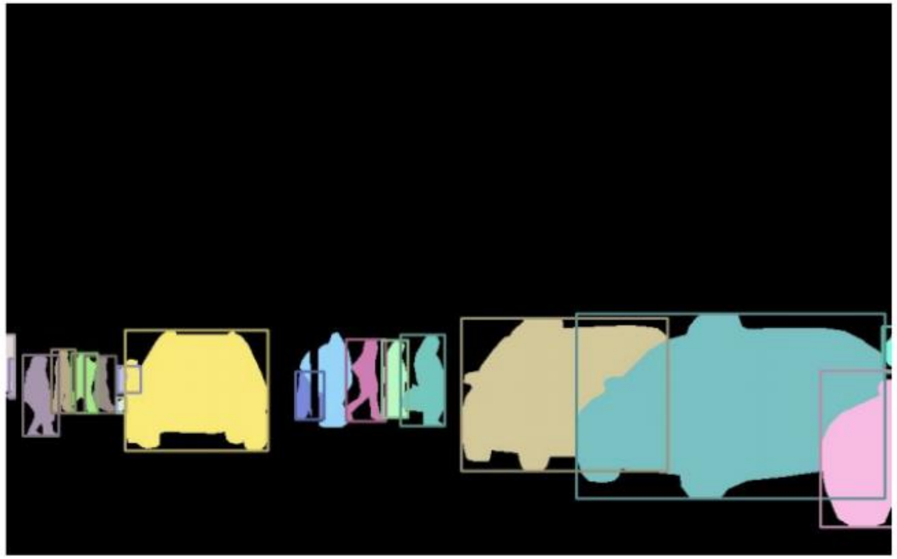
➢Example: All cars in the image → labeled as “Car” (same color in mask).

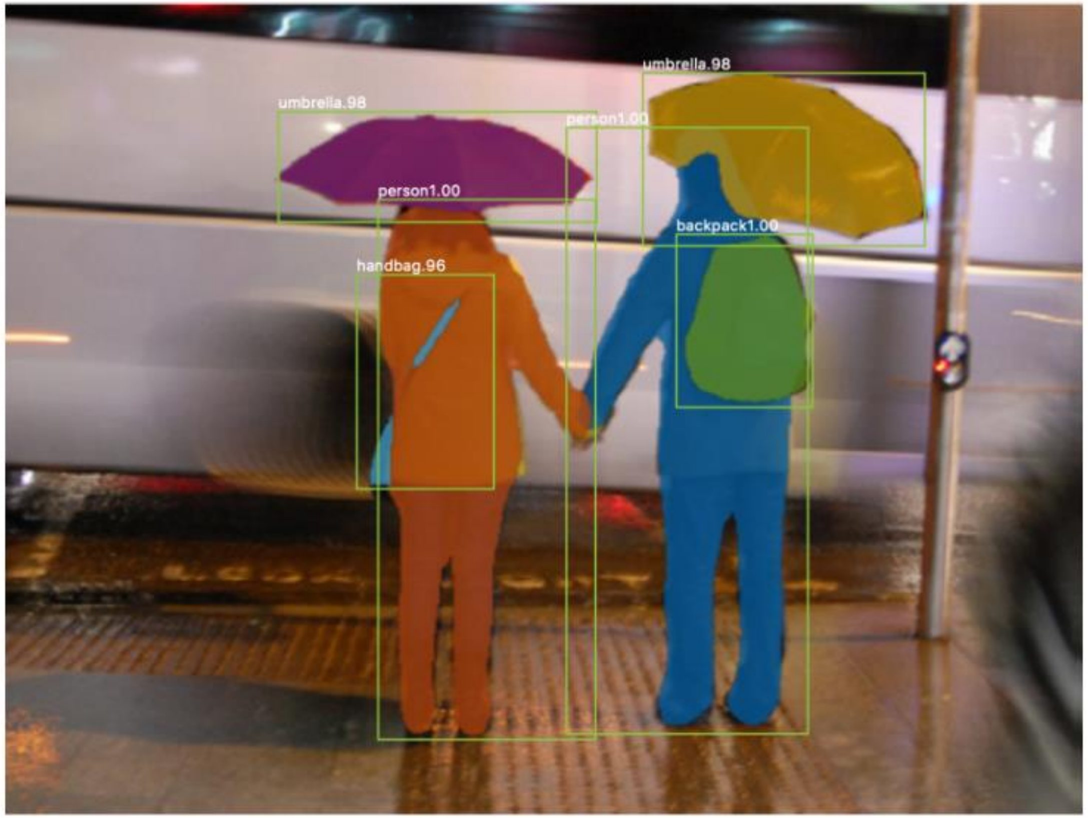
✓Limitation: Cannot distinguish **different instances** of the same class.



From Classification to Segmentation

- **Segmentation Types: Semantic vs. Instance**
  - **Segmentation Types in Computer Vision**
    - **2. Instance Segmentation**





✓Assigns **class + instance ID** to each pixel.

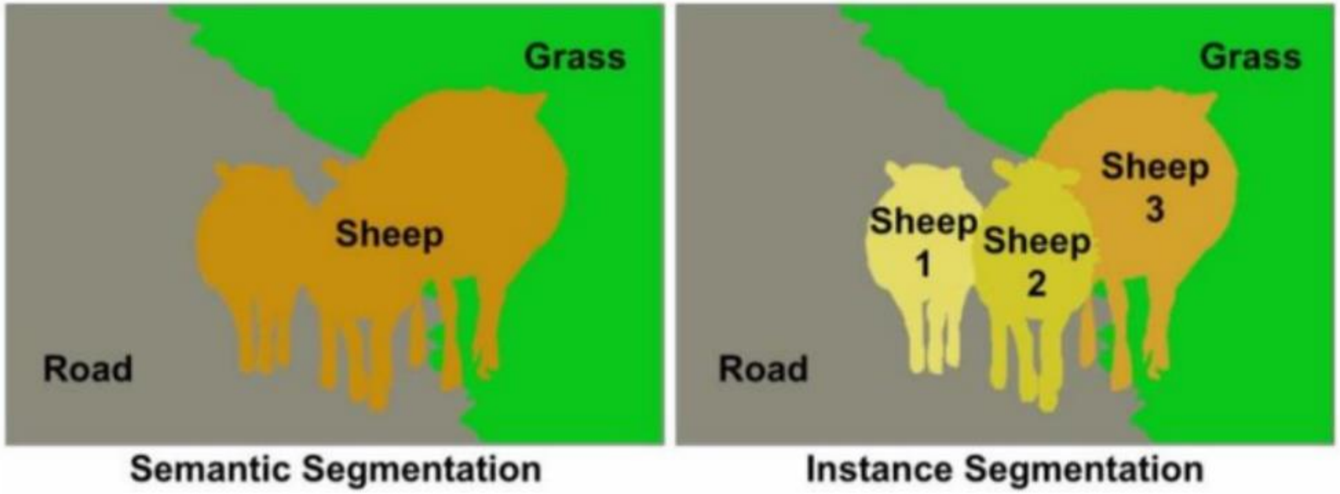
✓Objects with the same class but different instances have **separate masks**.

➢Example: Two cars → both "Car" class, but with different colors/masks (i.e., different id – car1 and car2).

✓Combines object detection's **localization** with segmentation's **pixel-level detail**.

From Classification to Segmentation

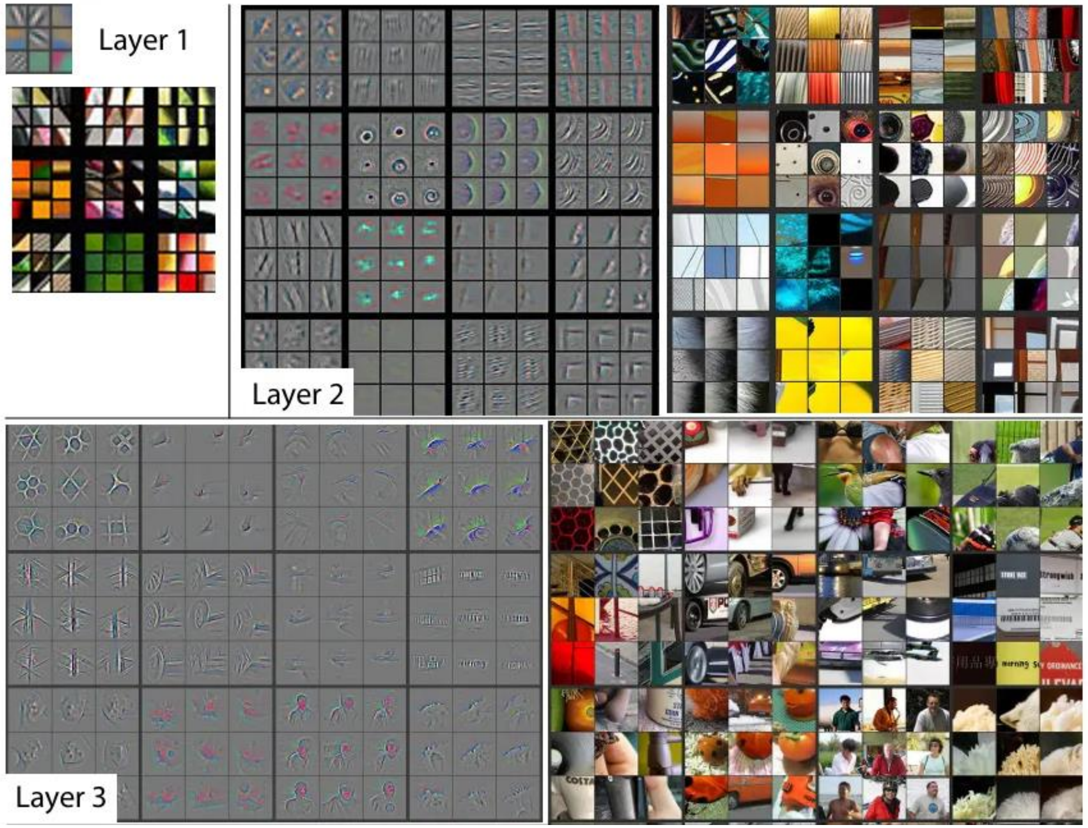
- Segmentation Types: Semantic vs. Instance
  - Segmentation Types in Computer Vision
    - Key Differences



Aspect	Semantic Segmentation	Instance Segmentation
Output Label	Class ID per pixel	Class ID + Instance ID per pixel
Same-class objects	Same label	Different labels (instance-aware)
Example Use Cases	Road scene parsing, medical imaging	Autonomous driving, object counting

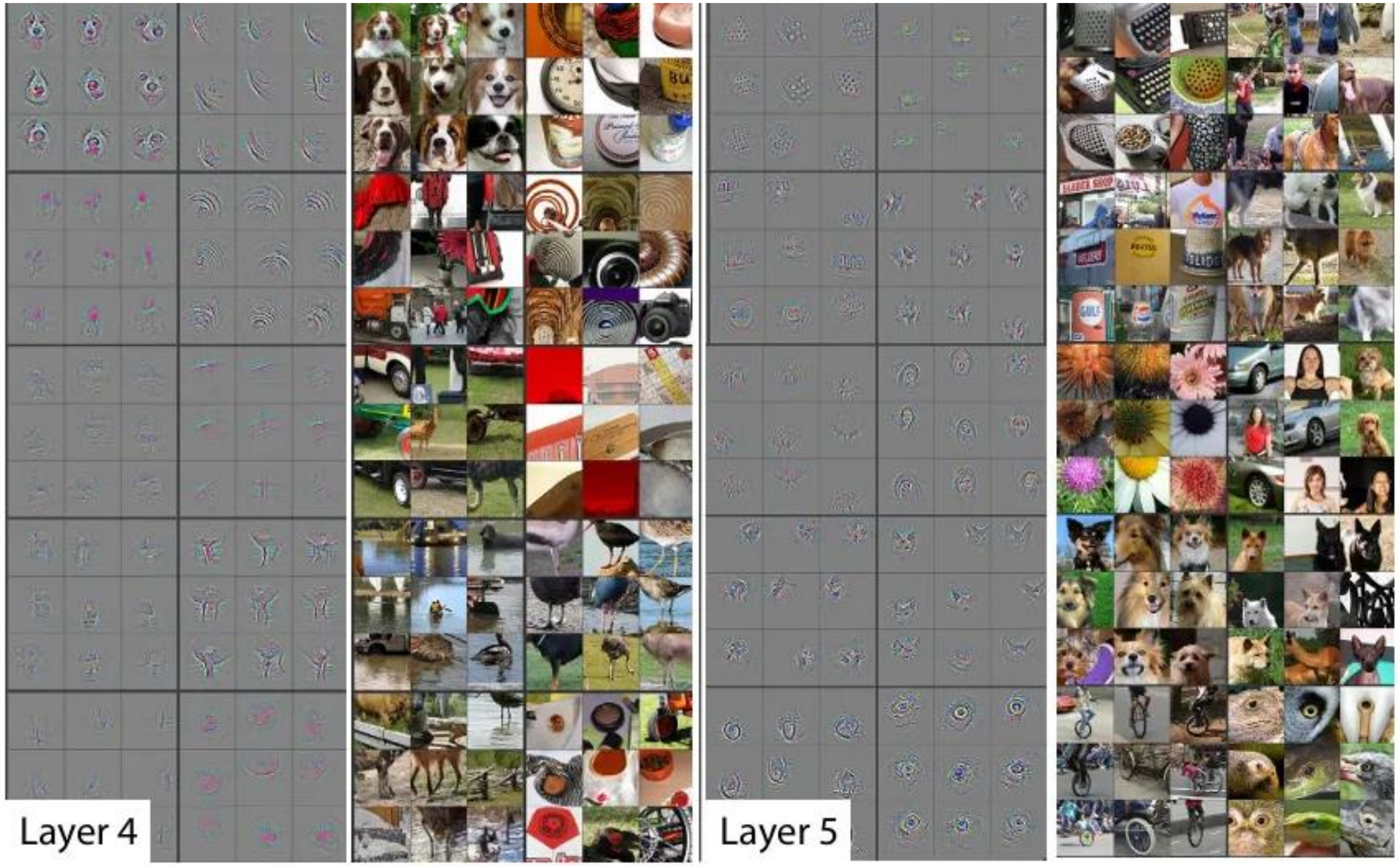
From Classification to Segmentation

- **Why Standard CNN Architectures for Classification Fail at Segmentation**
  - **1. How CNNs Learn Features**
    - **Early Layers – Low-Level Features**
      - ✓Learn basic visual patterns
        - ➢**Edges, corners, simple colors**.
      - ✓Capture fine-grained **spatial information**.
      - ✓Examples
        - ➢Layer 1 detects straight lines, edges at different orientations.
    - **Middle Layers – Mid-Level Features**
      - ✓Combine low-level patterns into **textures** and **object parts**.
      - ✓Example
        - ➢Layer 3 detects a dog's ear, a car wheel, or repeated surface patterns.



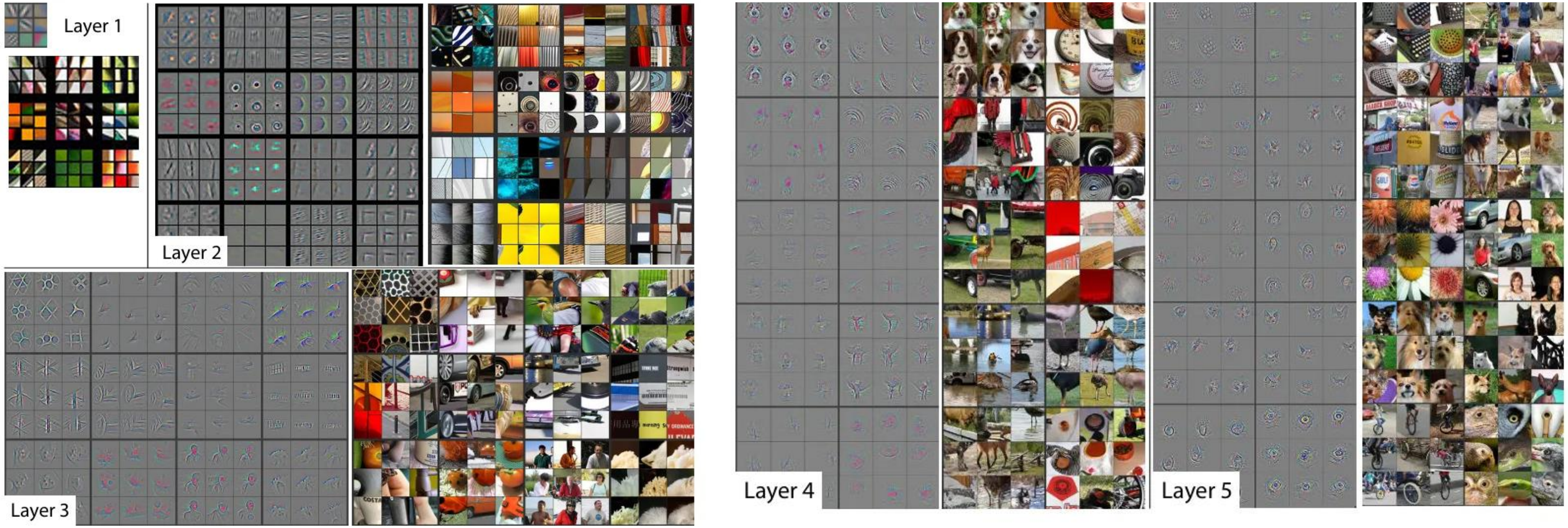
From Classification to Segmentation

- **Why Standard CNN Architectures for Classification Fail at Segmentation**
  - **1. How CNNs Learn Features**
    - **Deep Layers – High-Level Features**
      - ✓Detect **entire objects** or complex shapes.
      - ✓**Focus on semantic meaning** rather than precise location.
      - ✓Example
        - ➢Layer 5 activates for a whole dog or bicycle.



From Classification to Segmentation

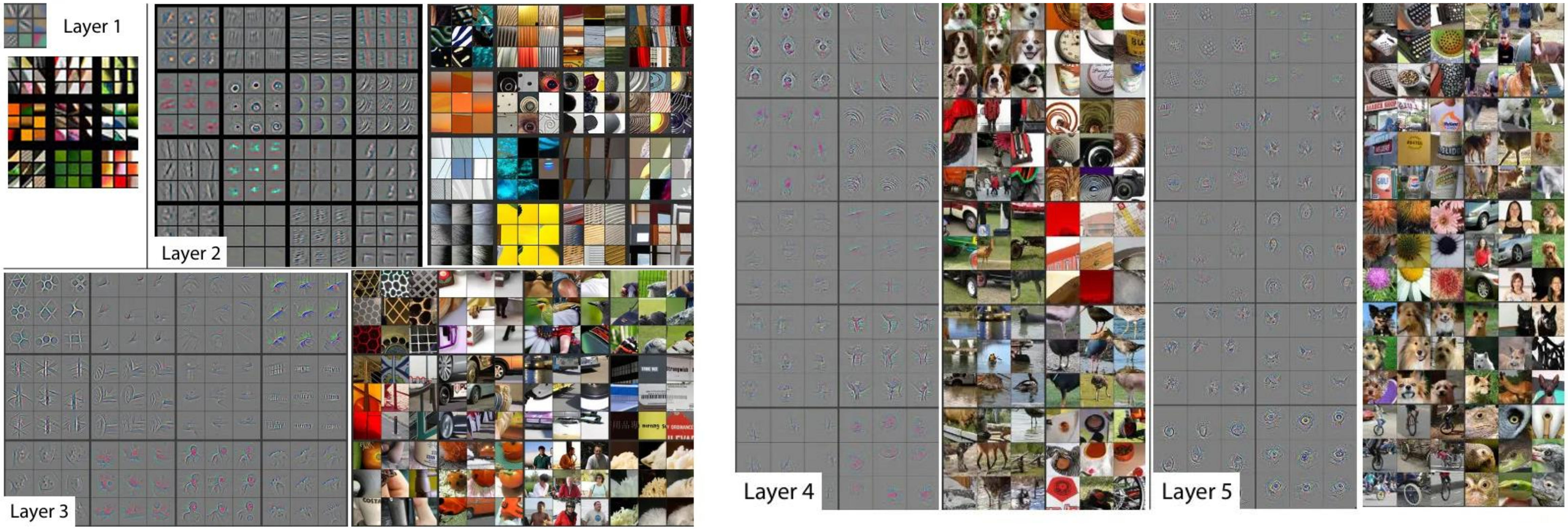
- **Why Standard CNN Architectures for Classification Fail at Segmentation**
  - **2. Important Observations for Segmentation**



- ***Standard CNN is "Translation Invariance"!***
  - ✓**1.** As we move deeper, **spatial resolution decreases** due to **pooling**, **stride**, and **downsampling**.
    - ➢***This leads to loss of spatial information → harder to know exact pixel positions.***
  - ✓**2. Fully connected layers discard almost all spatial info**.

From Classification to Segmentation

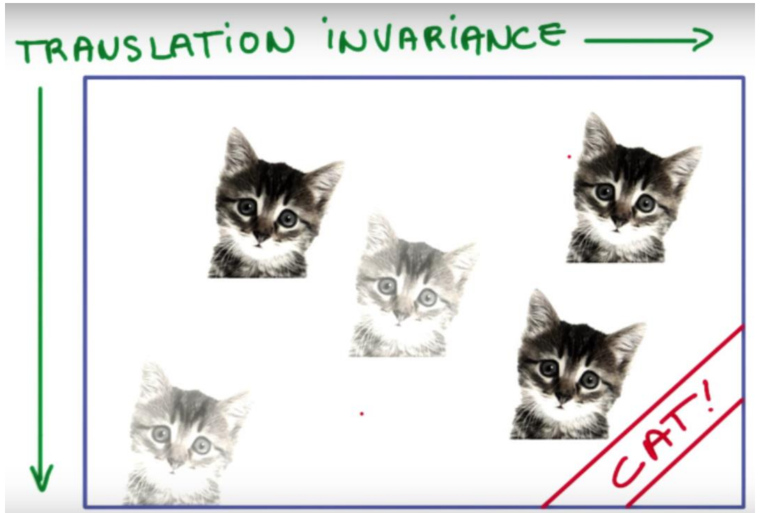
- **Why Standard CNN Architectures for Classification Fail at Segmentation**
  - **3. For segmentation, we need both for "*Translation Variance*"!**



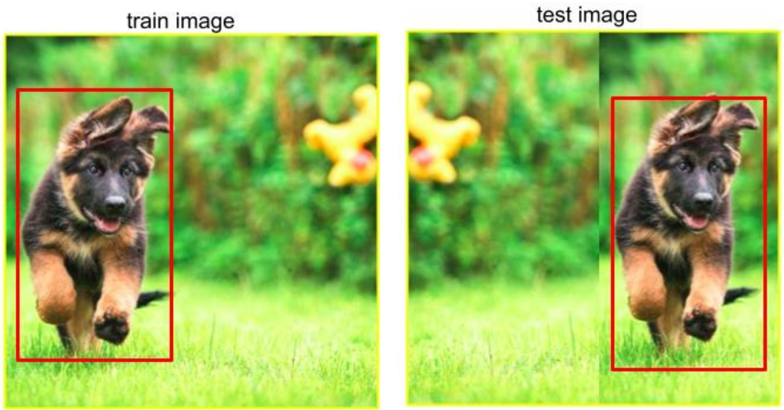
  - **1. Low-level features** → for precise boundaries (locality).
  - **2. High-level features** → for semantic understanding.

From Classification to Segmentation

- **How CNN Achieves Translation Invariance**
  - **1. Translation Equivariance vs. Translation Invariance**
    - **Equivariance:** Output changes position **in the same way** as input.
      - ✓Example: If a cat's face moves in the input, the feature map also moves.
    - **Invariance:** Output **remains the same** even if the input shifts.
      - ✓Example: A cat is still labeled "cat" no matter where it appears.

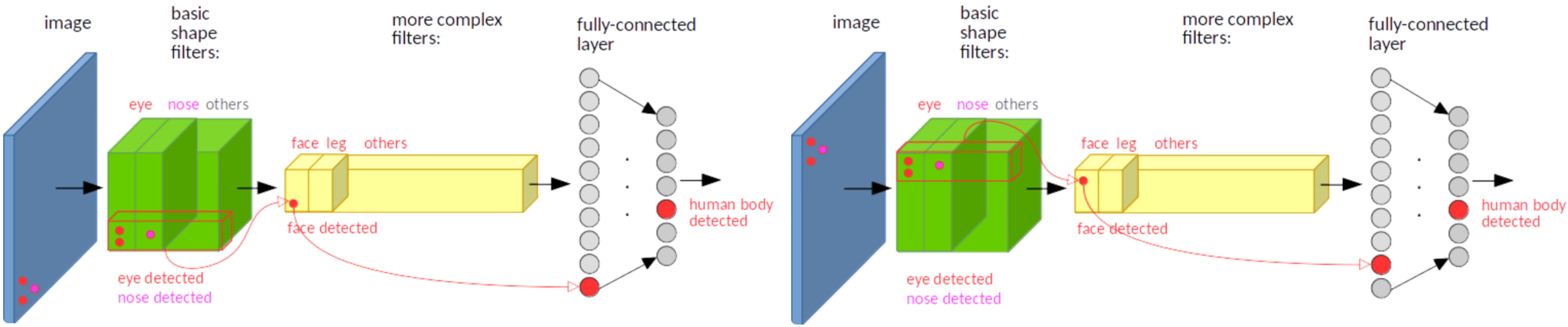


  - **2. Why CNN Has Translation Invariance**
    - Convolution operation → **translation equivariant** by nature.
    - **Weight sharing**: Same filters detect patterns anywhere in the image.
    - **Pooling**: Reduces sensitivity to small shifts (small-scale invariance).
    - **Fully connected layers + Softmax**: Final classification ignores position.



From Classification to Segmentation

- **How CNN Achieves Translation Invariance**
  - **3. Example Flow in CNN**

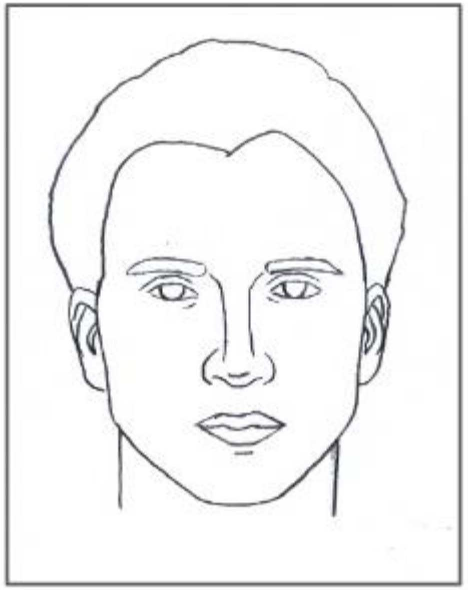


- **Early convolution layers**: Detect low-level features (eyes, nose) at exact positions → still equivariant.
- **Deeper convolution layers**: Combine features into higher-level patterns (face, leg).
- **FC layer & Softmax**: Output label probability is **position-independent** → invariant.

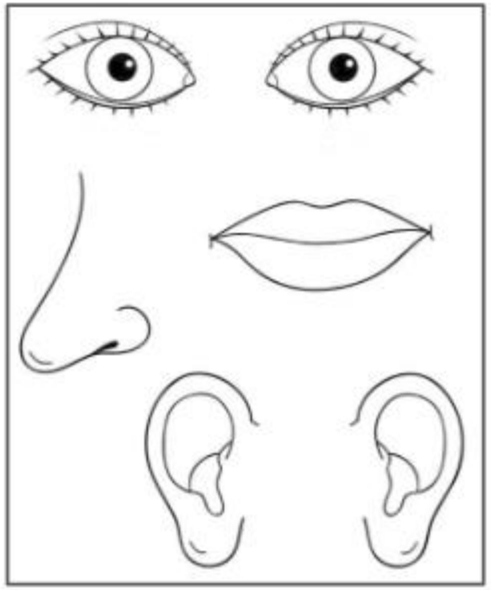
From Classification to Segmentation

- **How CNN Achieves Translation Invariance**
  - **4. Why This Matters**

Classification Task

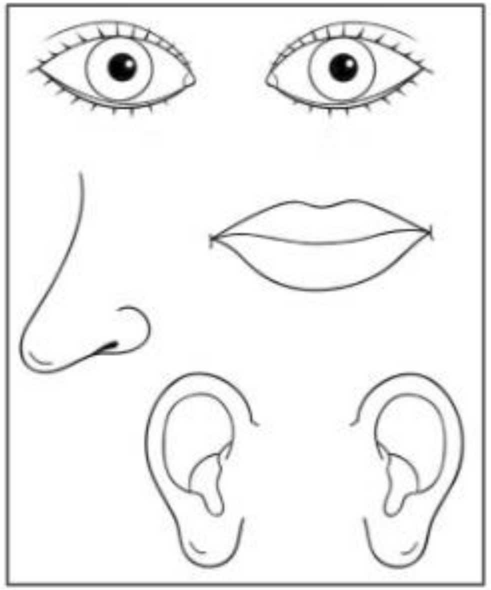


Face



Face

Segmentation Task



Not Face

- For **classification**: Translation invariance is beneficial.
- For **segmentation**: It can cause ***loss of locality***, harming pixel-level predictions.

From Classification to Segmentation

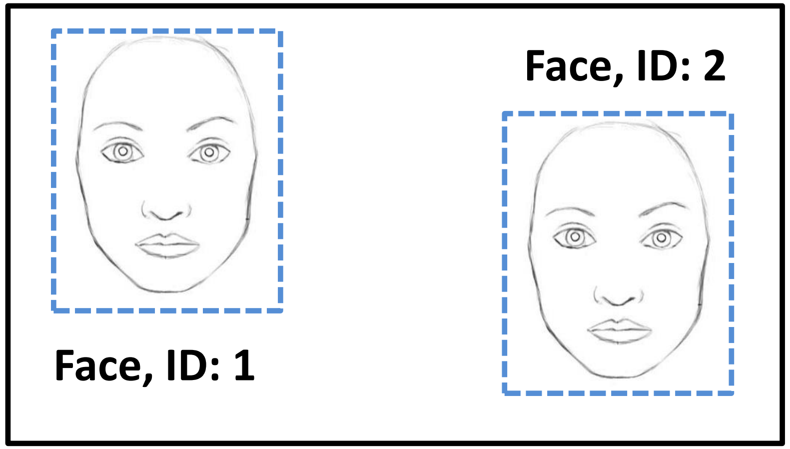
- **Detection Needs Translation Variance**
  - **Why Detection Needs Translation Variance**
    - **Classification:** Output label does not depend on location → *translation invariant*.
    - **Detection:** Must **localize** the object → output changes when the object moves.
    - **Translation variance** means the network output must change according to the object's position.

  - **Key Requirements for Detection**
    - ***Preserve Spatial Information***
      - ✓**Spatial information** = exact positional coordinates of features in the image.
      - ✓Allows model to determine *where* the object is located.
      - ✓Loss of spatial info → bounding boxes drift or fail completely.

    - ***Preserve Locality***
      - ✓**Locality** = maintaining the relationship between features **within a region** of the image.
      - ✓Important for capturing an object's **internal structure** (e.g., face = eyes + nose).

From Classification to Segmentation

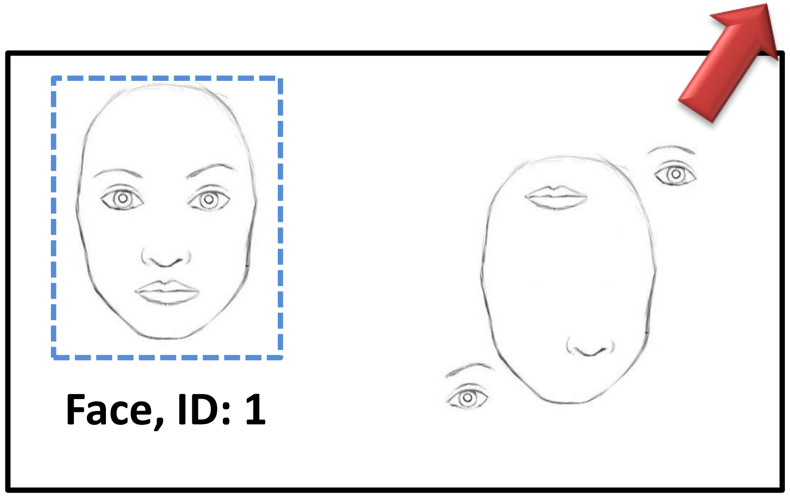
- **Detection Needs Translation Variance**
  - **Spatial Information vs. Locality – What's the Difference?**



Detected Object

Spatial Information-based Facial Identification

Not Detected



Detected Object

Locality-based Facial Identification

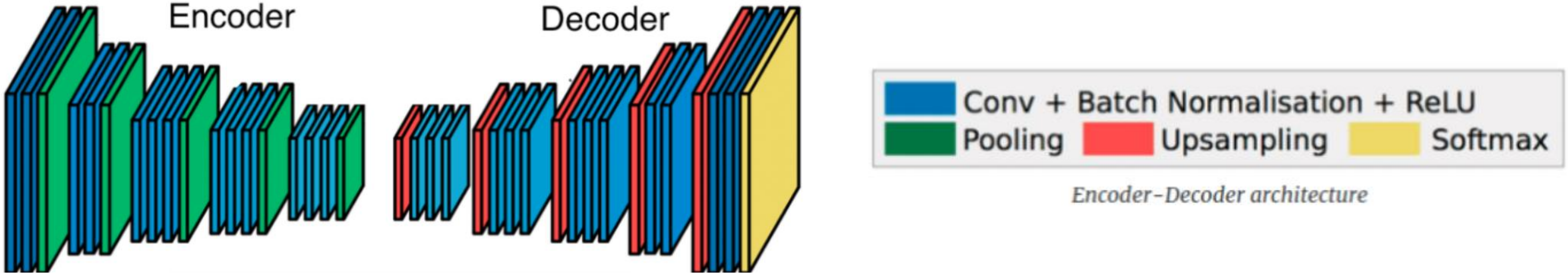
Term	Meaning	Example in Detection Task
Spatial Information	Absolute and relative coordinates of features in the image	"The face is at (x=150, y=200)"
Locality	Preservation of spatial relationships within a region	"The ears are above the eyes, the nose is b elow the eyes"

From Classification to Segmentation

- **How to Preserve Spatial Information and Locality**
  - **Problem Recap**
    - 1. Pooling & stride in CNN → **downsampling** → loss of spatial resolution.
    - **2. Spatial information**: Absolute position of features in the image.
    - **3. Locality**: Relative arrangement of features within a region.
    - 4. Loss of either → blurry boundaries & inaccurate localization.

From Classification to Segmentation

- **How to Preserve Spatial Information and Locality**
  - **Solution 1: Encoder–Decoder Structure**

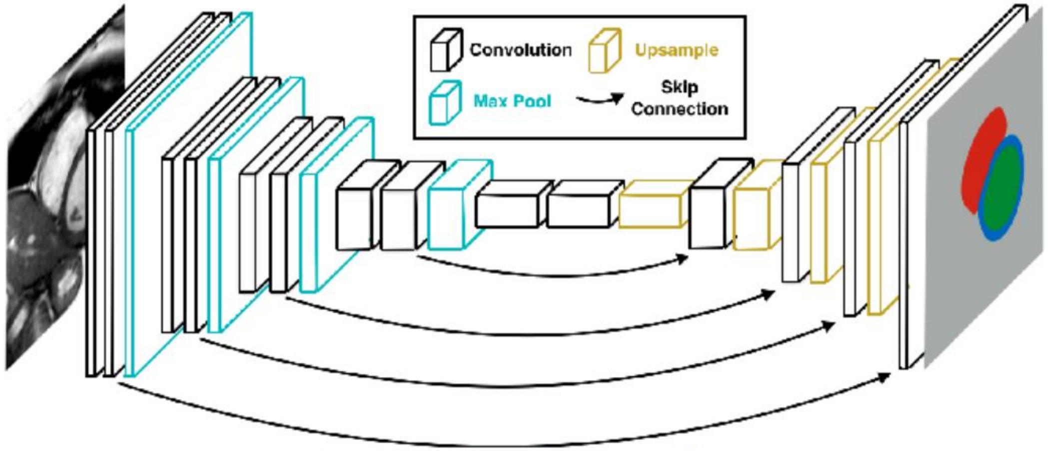


Encoder–Decoder architecture

- **Encoder**
  - ✓Uses **convolutions + pooling** to extract high-level semantic features.
  - ✓Gradually reduces spatial dimensions ($\boldsymbol{W} \times \boldsymbol{H} \ \rightarrow \ \boldsymbol{w} \times \boldsymbol{h}$).
- **Decoder**
  - ✓Uses **upsampling** to restore feature maps to original size ($\boldsymbol{w} \times \boldsymbol{h} \ \rightarrow \ \boldsymbol{W} \times \boldsymbol{H}$).
  - ✓Generates segmentation map where each pixel has a class label.
- **Problem in Simple Encoder–Decoder**
  - ✓High-level features from encoder lack **low-level details** (edges, fine structures).
  - ✓Upsampling alone cannot reconstruct precise boundaries.

From Classification to Segmentation

- **How to Preserve Spatial Information and Locality**
  - **Solution 2: Skip Connections**



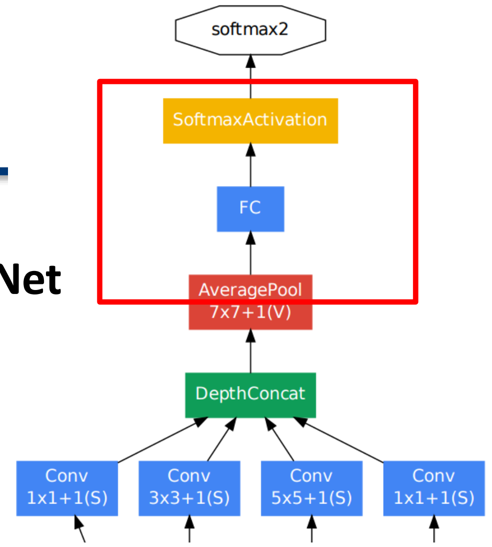
Encoder–Decoder with skip connections

- ○ Directly connect encoder layers to corresponding decoder layers.
- ○ Merge **low-level spatial details** from encoder with **high-level semantics** from decoder.
- ○ Restores sharp object boundaries and preserves locality.
- ○ **Benefits**
  - ✓Retain **low-level details** (edges, textures).
  - ✓Preserve **spatial resolution** across network.
  - ✓Combine **locality** + **semantic context** for accurate segmentation.

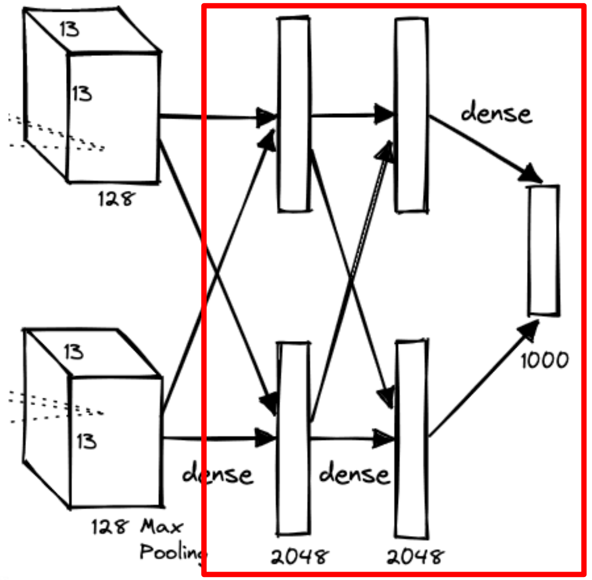
Introduction to Fully Convolutional Networks (FCNs)

- **Fully Convolutional Networks for Semantic Segmentation**
  - **Goal**
    - Perform **semantic segmentation**: assign a **class label to every pixel** in an image.
    - Achieve **end-to-end learning** from input image to dense output.
    - Balance **semantic meaning** (*what is present*) with **spatial precision** (*where it is located*).
  - **Key Idea**
    - Transform existing high-performing classification CNNs (e.g., **AlexNet, VGG, GoogLeNet**) into **fully convolutional networks**.
    - ***Replace fully connected layers with convolutional layers to preserve spatial information***.
    - Adapt these networks for **dense prediction** tasks.

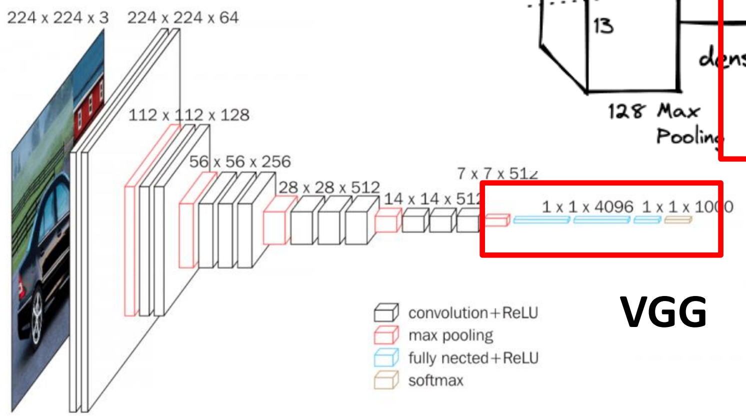
Fully-connected layers



GoogleNet



AlexNet



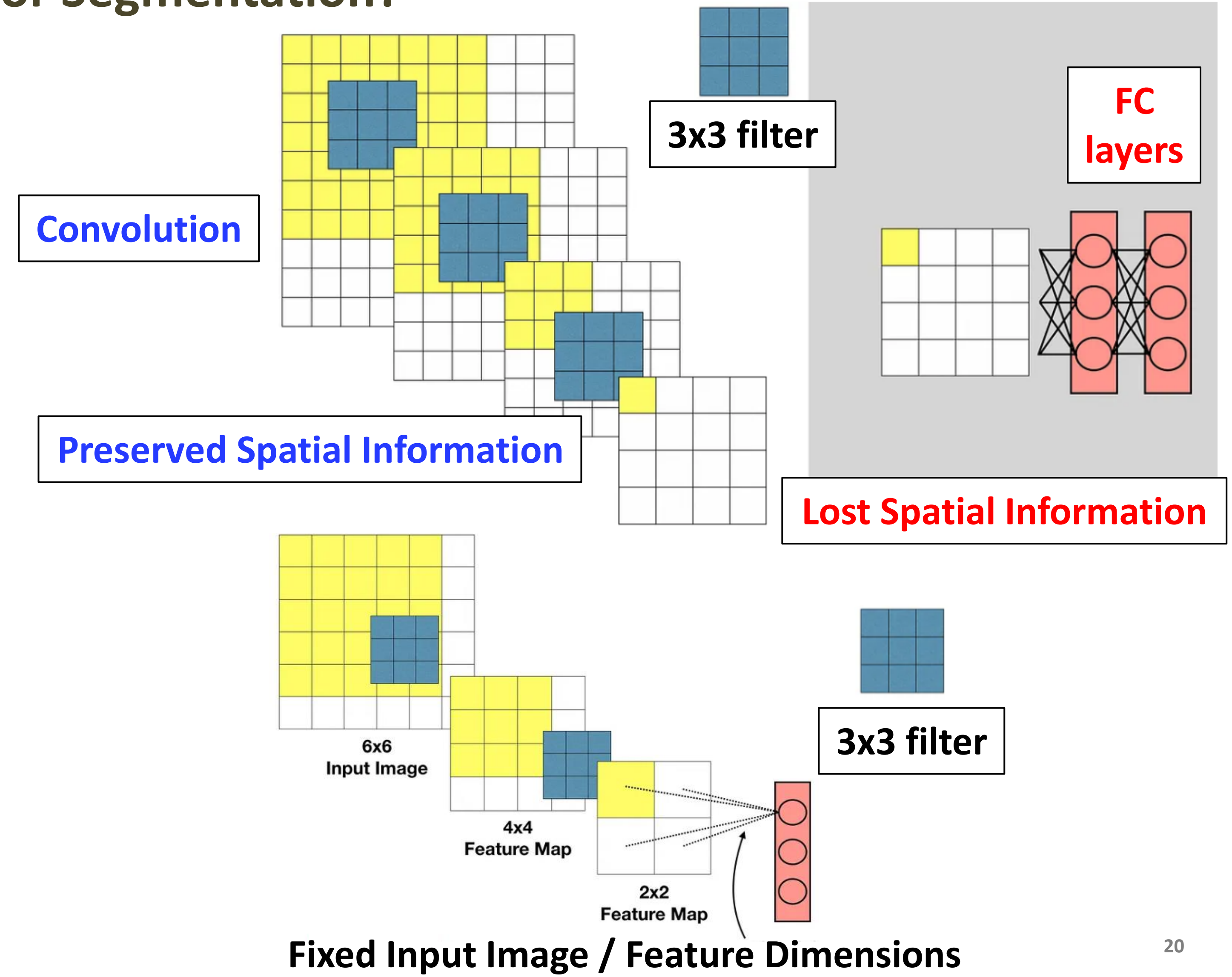
VGG

Introduction to Fully Convolutional Networks (FCNs)

- **Fully Convolutional Networks for Semantic Segmentation**
  - **Key Insight**
    - **Fully Convolutional Design**
      - ✓1. Accepts **arbitrary-sized inputs**.
      - ✓2. Produces outputs of **corresponding spatial size**.
      - ✓3. Enables **efficient whole-image training & inference**.
    - Avoids complex pre/post-processing (superpixels, proposals, CRFs).
    - Fine-tune from supervised pre-training for strong initial feature representations.
  - **Core Steps**
    - **Convolutionalization**
      - ✓Replace fully connected layers with equivalent convolution layers.
      - ✓Maintain spatial correspondence and allow variable input sizes.
    - **Upsampling (Deconvolution)**
      - ✓Convert coarse feature maps into dense, high-resolution predictions.
    - **Skip Architecture**
      - ✓Fuse **deep, coarse, semantic** features with **shallow, fine, appearance** features for accurate boundaries.

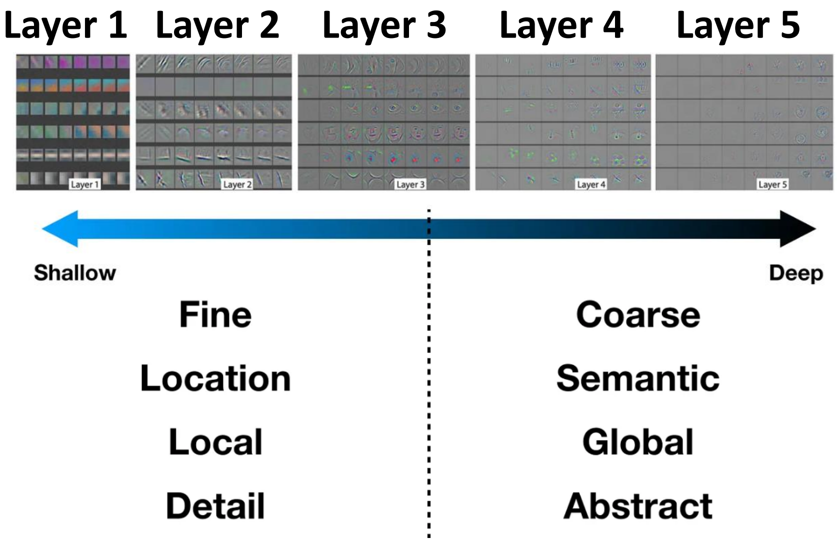
Convolutionalization: Motivation

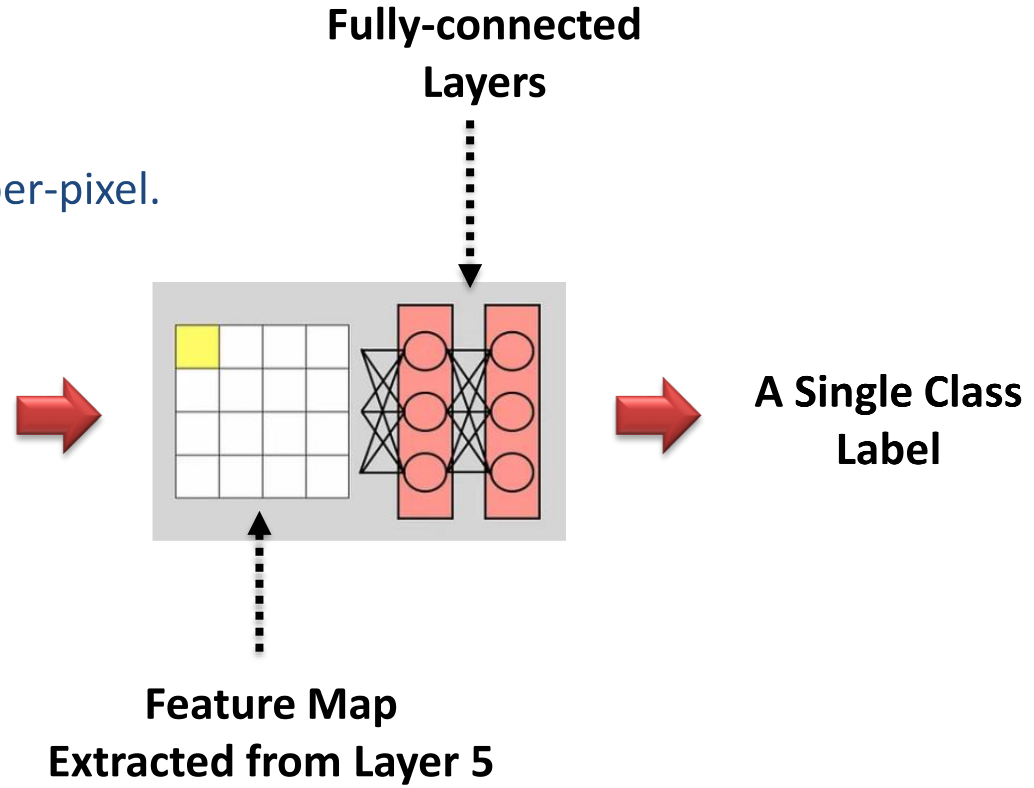
- **Why Replace Fully Connected Layers for Segmentation?**
  - **Problems with Fully Connected Layers**
    - **1. Loss of Spatial Information**
      - ✓FC layers flatten feature maps, discarding pixel location data.
      - ✓Critical spatial correspondences (what is where) are lost.
    - **2. Fixed Input Size Constraint**
      - ✓FC layers require a fixed vector size → fixed input image dimensions.
      - ✓Limits flexibility for variable-sized images.



Convolutionalization: Motivation

- **Why Replace Fully Connected Layers for Segmentation?**
  - **Problems with Fully Connected Layers**
    - **3. Coarse Outputs for Dense Prediction**
      - ✓**Output is a single class label** for the whole image, not per-pixel.

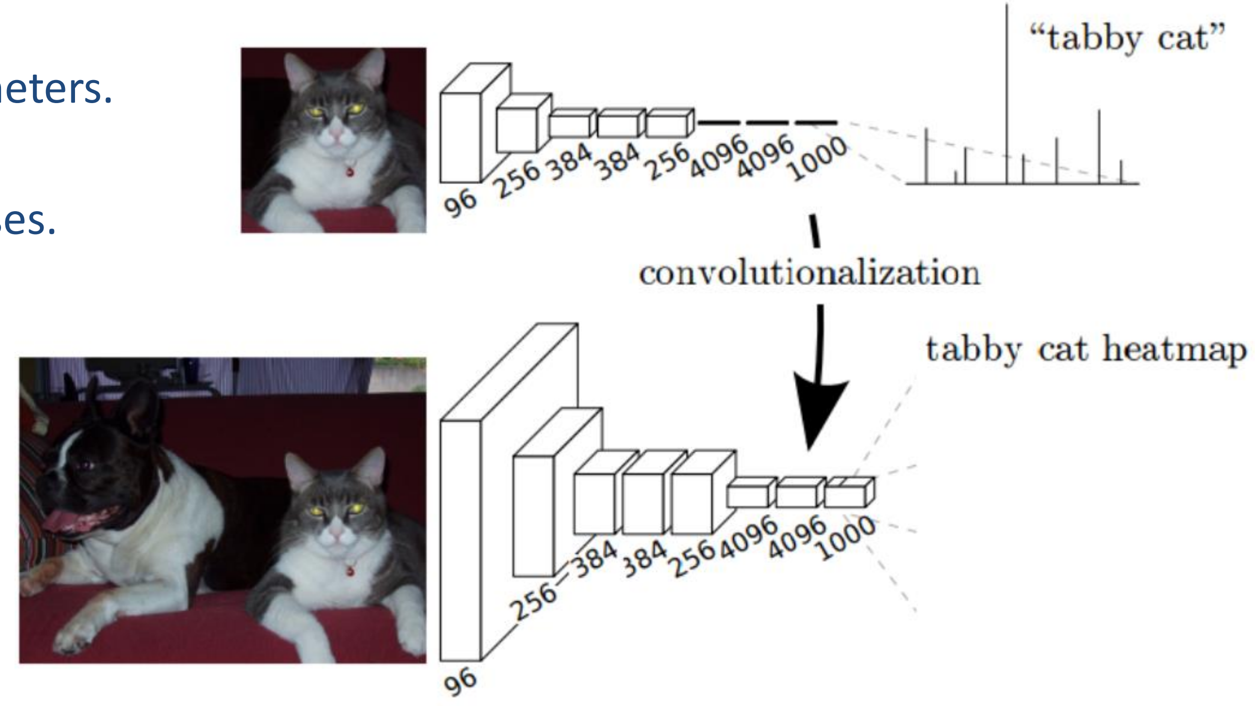




- **Summary – Why This is a Problem for Segmentation**
  - ✓1. Semantic segmentation needs **dense, pixel-to-pixel predictions**.
  - ✓2. Requires **both semantic meaning** (what the object is) **and location information** (where it is).
  - ✓3. FC layers destroy the "where" component.

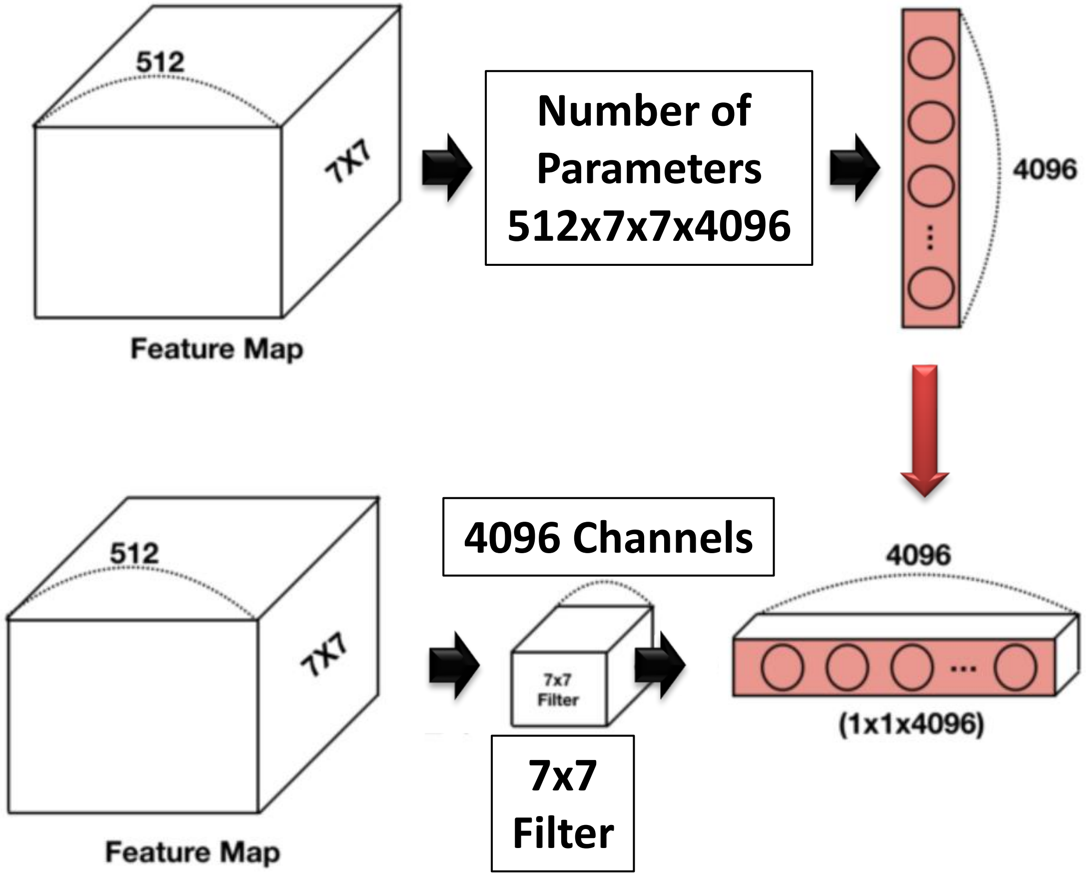
Convolutionalization: Motivation

- **Why Replace Fully Connected Layers for Segmentation?**
  - **The FC-to-Conv Transformation (*Convolutionalization*)**
    - Replace FC layers with **equivalent convolutional layers**.
      - ✓Example: VGG16's first FC layer
        → 7×7 Conv layer with the same number of parameters.
      - ✓Final FC layer
        → **1×1 Conv layer** with channels = number of classes.
    - Benefits
      - ✓**(1)** Accepts **arbitrary input sizes**
      - ✓**(2)** Produces **spatial output maps** that preserve location cues
      - ✓**(3)** Enables **end-to-end pixel-level learning**.



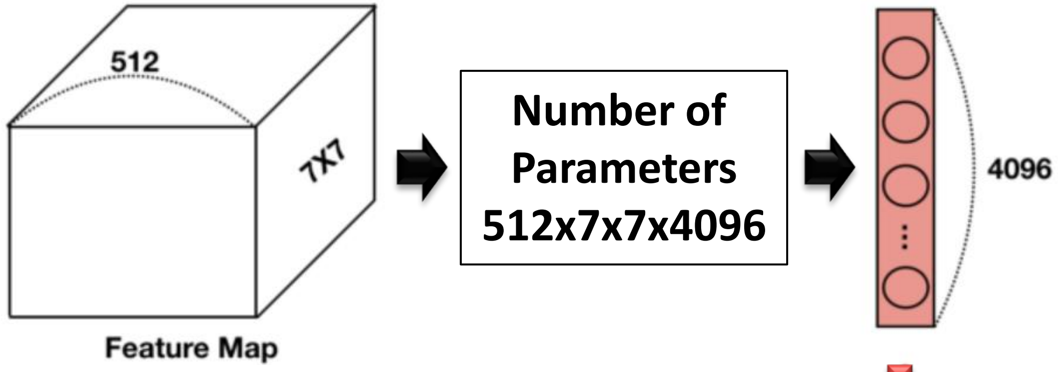
Convolutionalization: Motivation

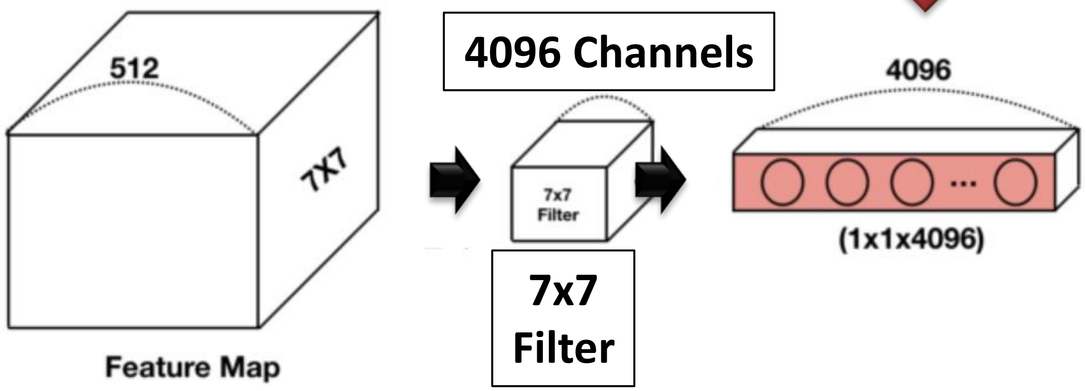
- **Why Replace Fully Connected Layers for Segmentation?**
  - **The FC-to-Conv Transformation (*Convolutionalization*)**
    - **Example: Replacing FC Layers with Convolutional Layers**
      - ✓ **Problem with FC Layers**
        - ➢ Fixed input dimension
          (e.g., VGG-16 requires a vector of length **4096**).
        - ➢ Spatial coordinates are lost when flattening.
      - ✓ **Key Idea**
        - ➢ Treat an FC layer as a **convolution**
          with a kernel covering the entire input feature map.
        - ➢ Replace
          - First FC layer
            → **7×7 Conv** with 4096 filters.
          - Final FC layer
            → **1×1 Conv** with channels = number of classes.



Convolutionalization: Motivation

- **Why Replace Fully Connected Layers for Segmentation?**
  - **The FC-to-Conv Transformation (*Convolutionalization*)**
    - **Example: Replacing FC Layers with Convolutional Layers**
      - ✓ **VGG-16 Example**
        - ➢ **Before**
          - Input feature map: **7×7×512**.
          - Flatten to 1×1×(512×7×7) = 1×1×25088.
          - Fully Connected to 4096 units.
        - ➢ **After**
          - Apply **7×7 Conv** (512 input channels, 4096 filters) → Output **1×1×4096**.
          - Spatial structure is preserved for larger inputs.



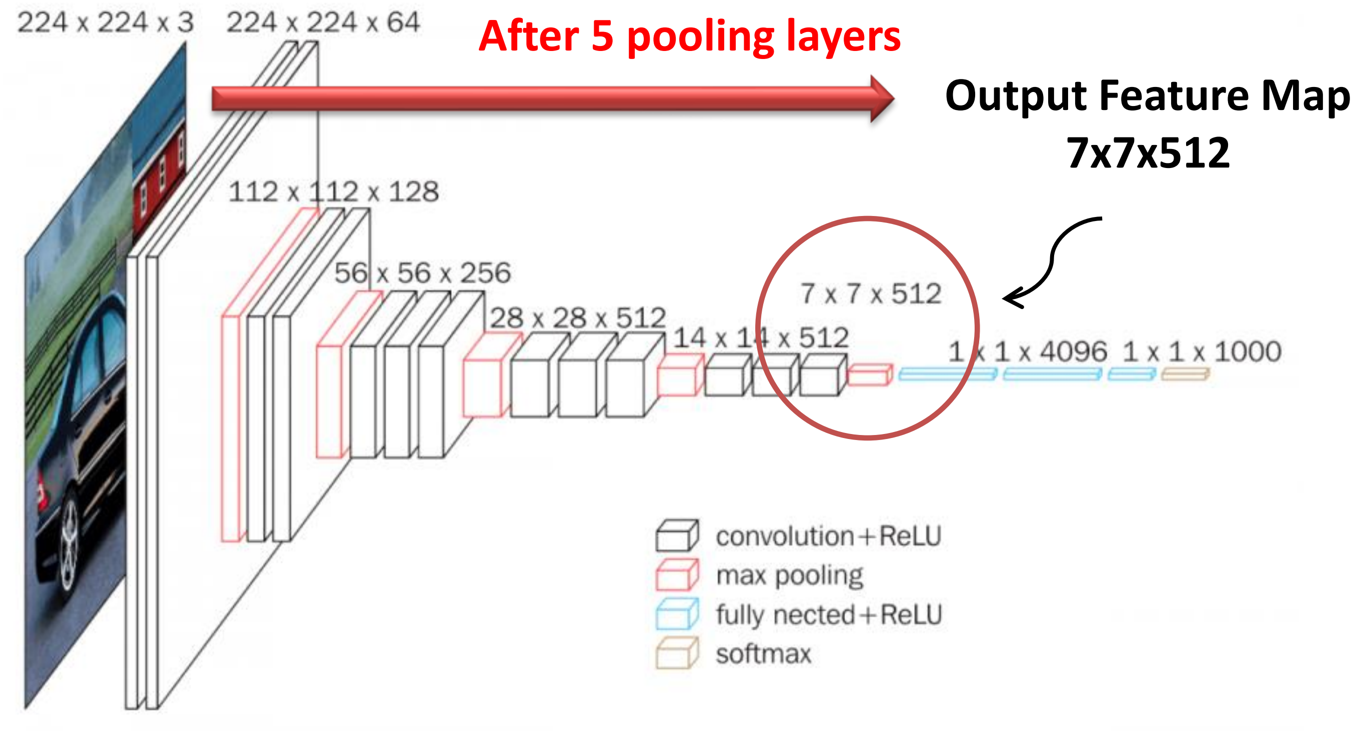


      - ✓ **Advantages**
        - ➢ Works with **any input size** (no FC size constraint).
        - ➢ Produces **spatial output maps**
          → essential for segmentation.
        - ➢ Computation is **faster** for large images
          → ≈ 5× speedup over patch-by-patch.

Coarse Outputs and the Need for Upsampling

- **Why Upsampling is Essential for Segmentation**
  - **1. Downsampling in CNNs**
    - **Pooling layers** and **strided convolutions** progressively reduce spatial resolution.

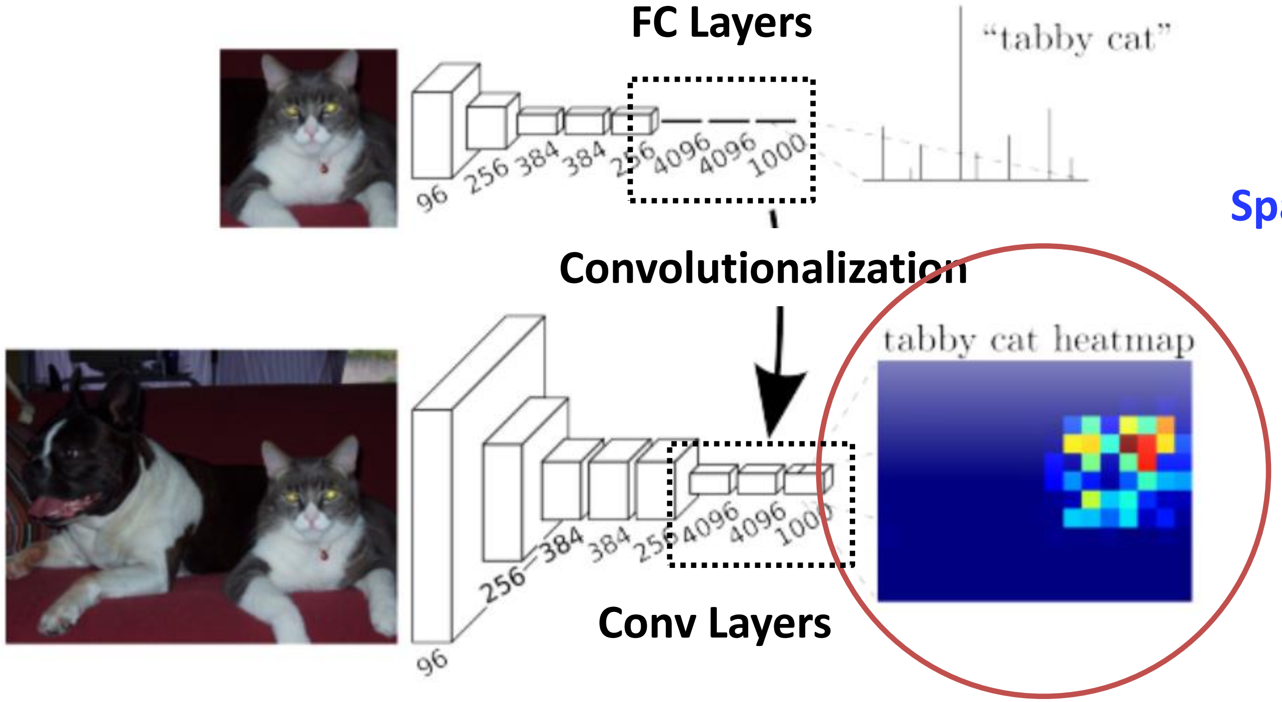
Input Image
224x224x3
(RGB)



    - Example: VGG-16
      - ✓Input: **224×224**
      - ✓After 5 pooling layers (stride 2 each) → Output feature map: **7×7**
      - ✓This is a **stride 32** reduction.

Coarse Outputs and the Need for Upsampling

- **Why Upsampling is Essential for Segmentation**
  - **2. The Problem for Segmentation**



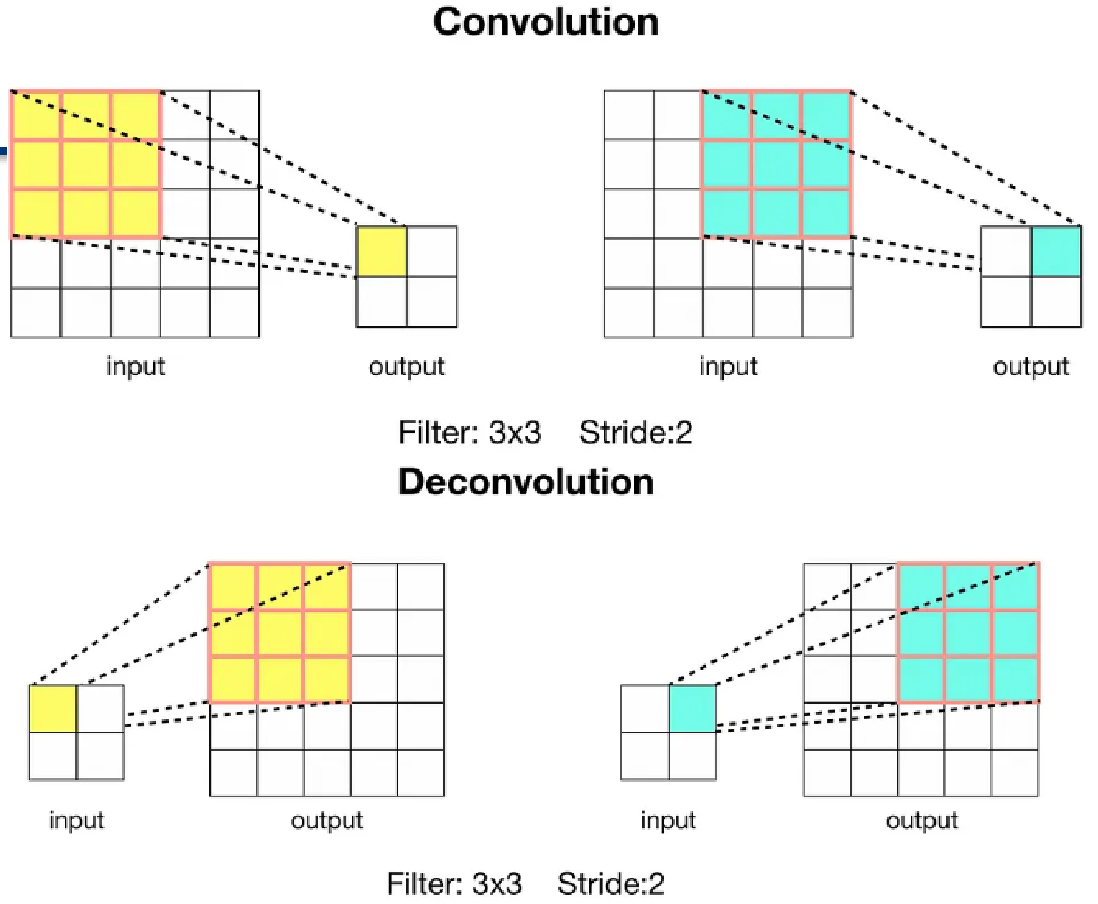
Spatial Information is preserved.

Resolution is still coarse.

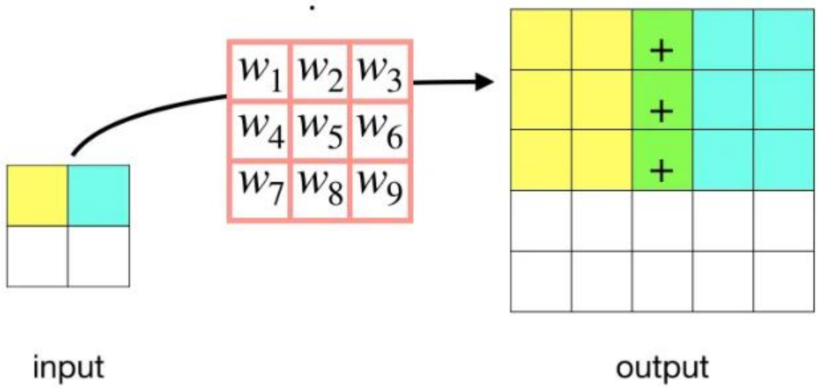
- Fully convolutional conversion preserves spatial **arrangement**, *but* ***resolution*** *is still* ***coarse***.
- For pixel-wise prediction, we need **near-original resolution** output.
- Without upsampling, fine details and object boundaries are lost.

Upsampling with Learnable Deconvolution

- **From Coarse to Dense: Deconvolution Layers**
  - **1. Upsampling Methods**
    - ○ **Fixed**
      - ✓**Bilinear Interpolation**
        - ➢Simple, non-learnable resizing.
      - ✓**Unpooling**
        - ➢Reverses pooling using stored indices.
    - ○ **Learnable**
      - ✓**Deconvolution**
        (=Transposed Convolution, Backwards Convolution)
        - ➢ Parameters learned during training.
  - **2. Backwards Convolution Concept**
    - ○ Standard convolution (stride > 1) **reduces** spatial size (downsampling).
    - ○ Reversing this process **increases** spatial size (upsampling).
    - ○ Uses **learnable filters** so that the upsampling is **task-optimized**.



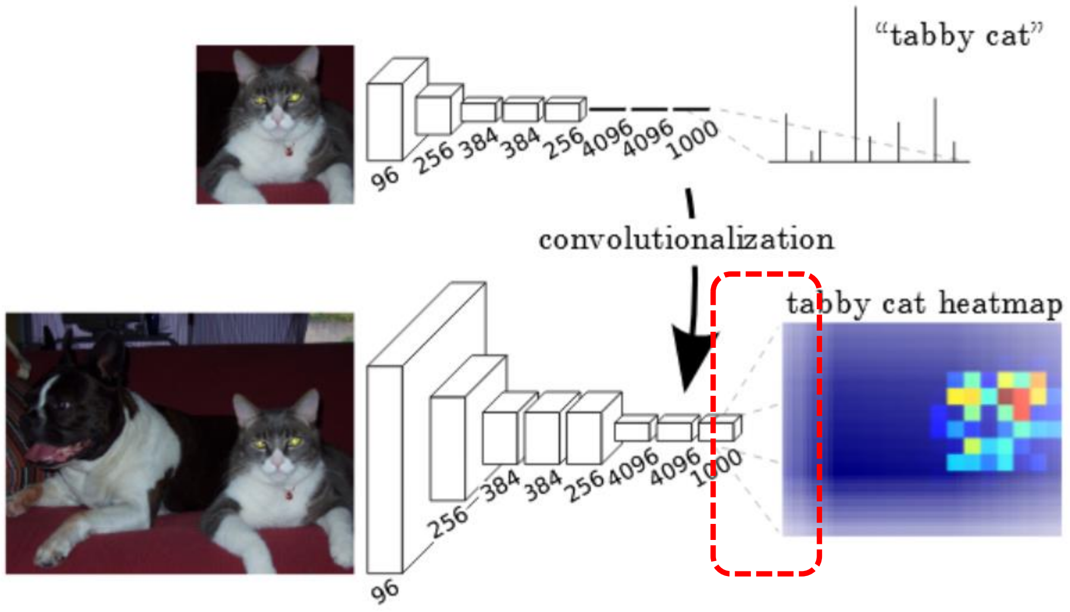
Overlapped Parameters are added.

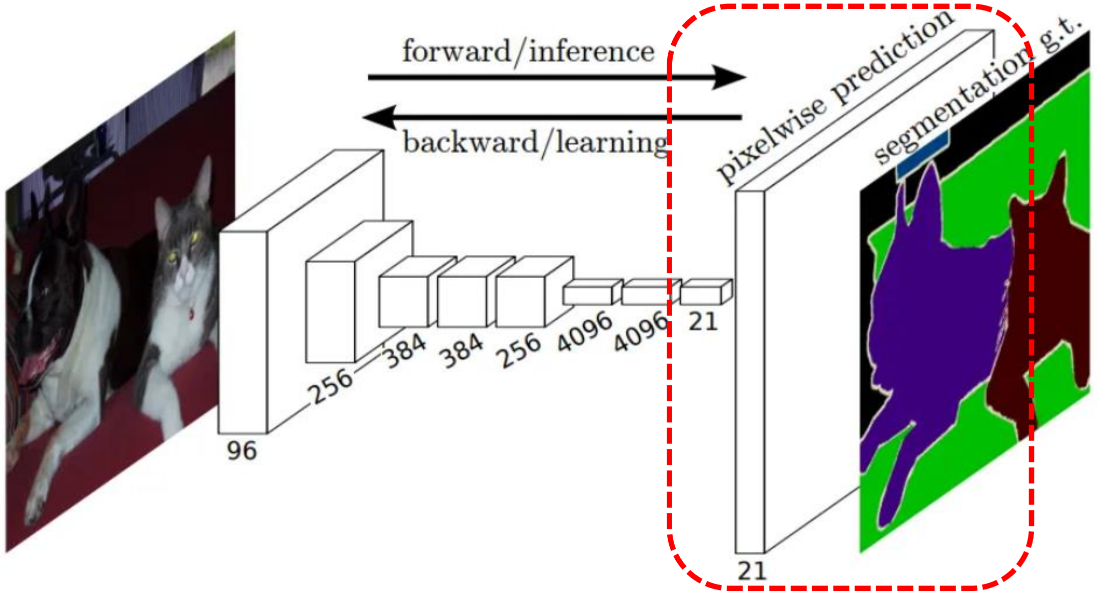


Upsampling with Learnable Deconvolution

- **From Coarse to Dense: Deconvolution Layers**
  - **How FCN Uses It**
    - *FCNs employ deconvolution layers for upsampling coarse feature maps to the input size.*
    - Initial weights are set to **bilinear interpolation** values.
    - During training, these weights are updated to improve segmentation accuracy.
    - Allows **end-to-end training** with pixel-wise loss.

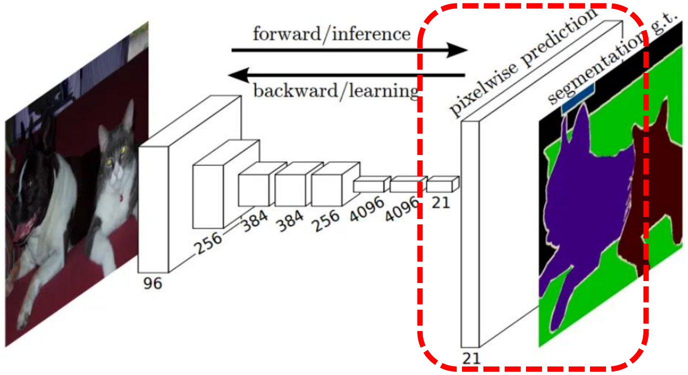
Deconvolution (i.e., upsampling)





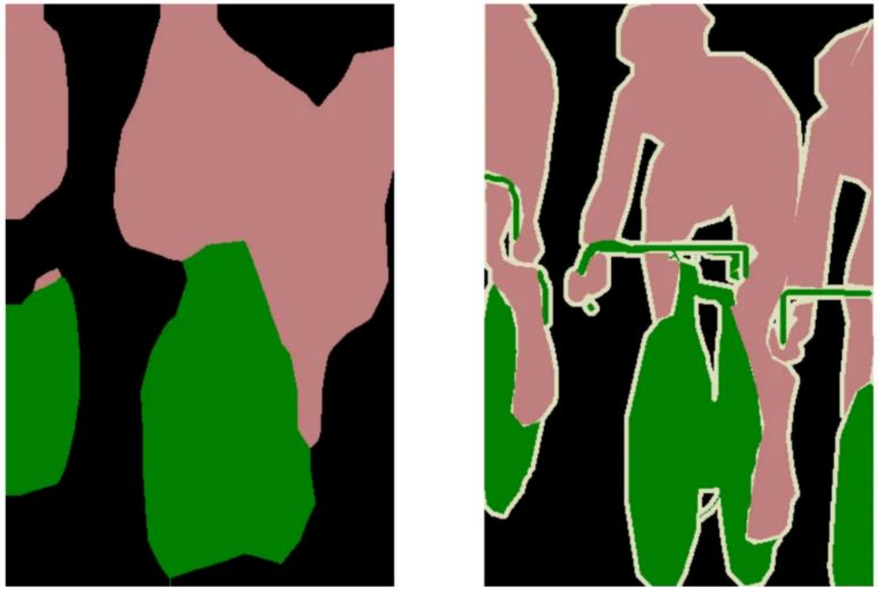
The Problem with Coarse Outputs

Deconvolution
(i.e., upsampling)



Why Coarse Outputs are Not Enough

- **Deconvolution alone is insufficient**
  - Even with trainable deconvolution, a coarse feature map (e.g., stride 32) lacks detailed spatial information.
- **Loss of detail**
  - Large stride means much information is lost during down sampling, leading to blurry and imprecise boundaries.
- **Example**
  - FCN-32s often produces smooth, rounded edges rather than accurate object contours.
- **Reason**
  - The receptive field covers a large area,
    so fine-grained boundaries from the original image are not preserved.

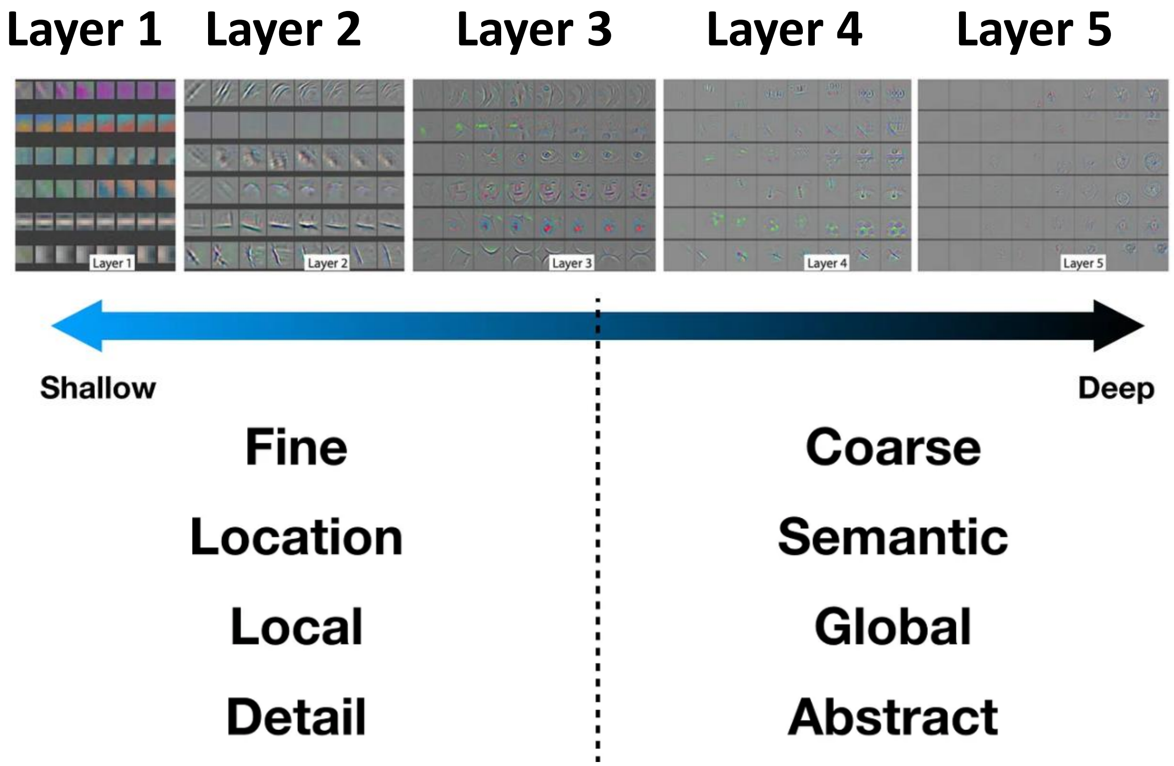


Prediction   Ground truth

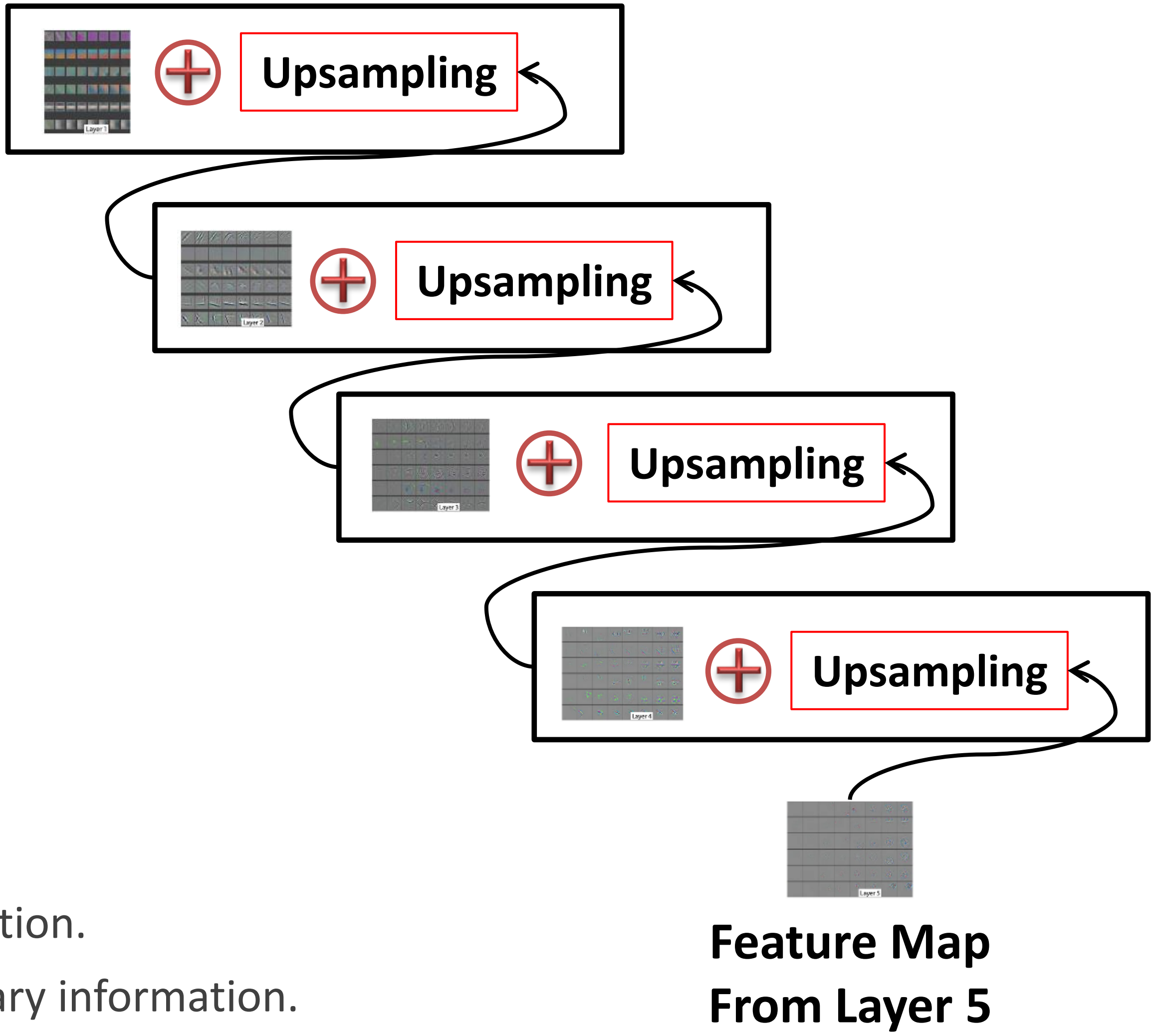
Loss of detail

Skip Architecture

- **Skip Architecture for Better Segmentation**
  - **Core idea –** Fuse

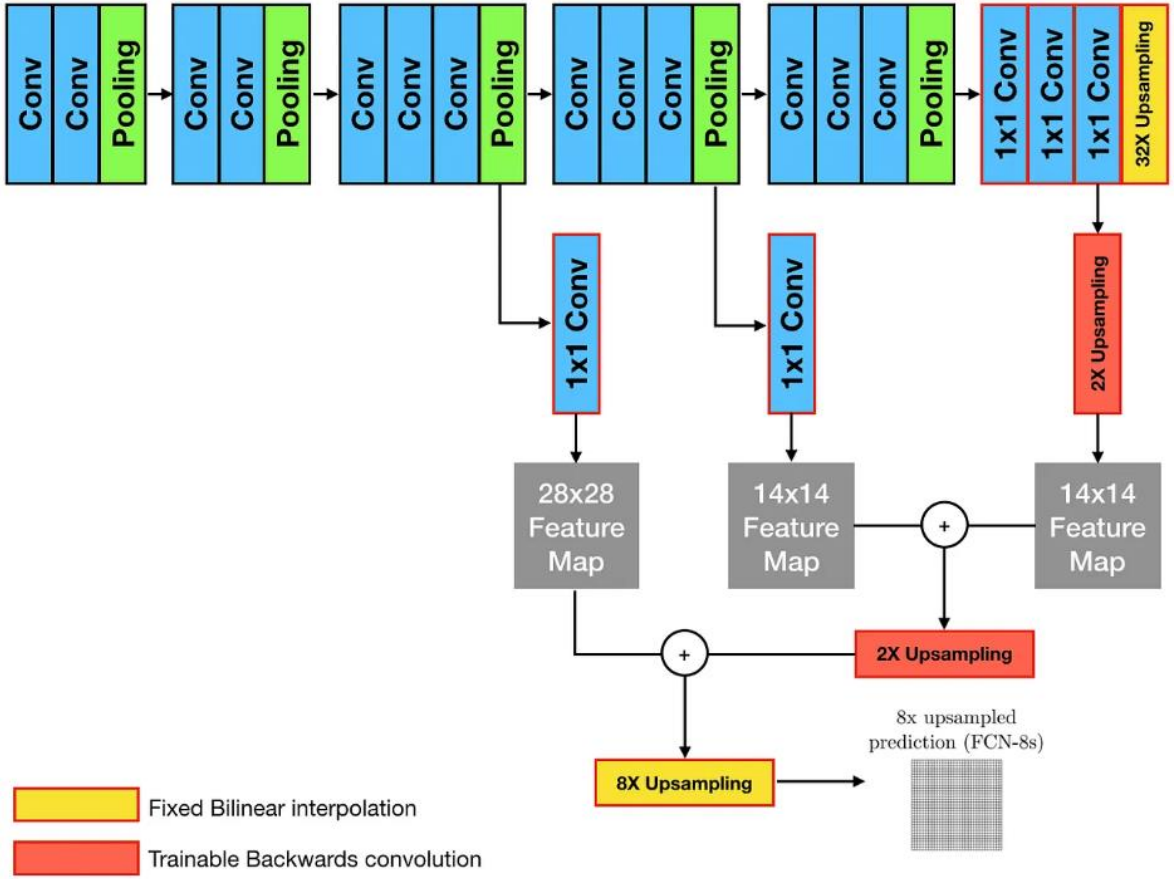


    - **Deep & coarse layers** → rich semantic (meaning) information.
    - **Shallow & fine layers** → detailed appearance and boundary information.

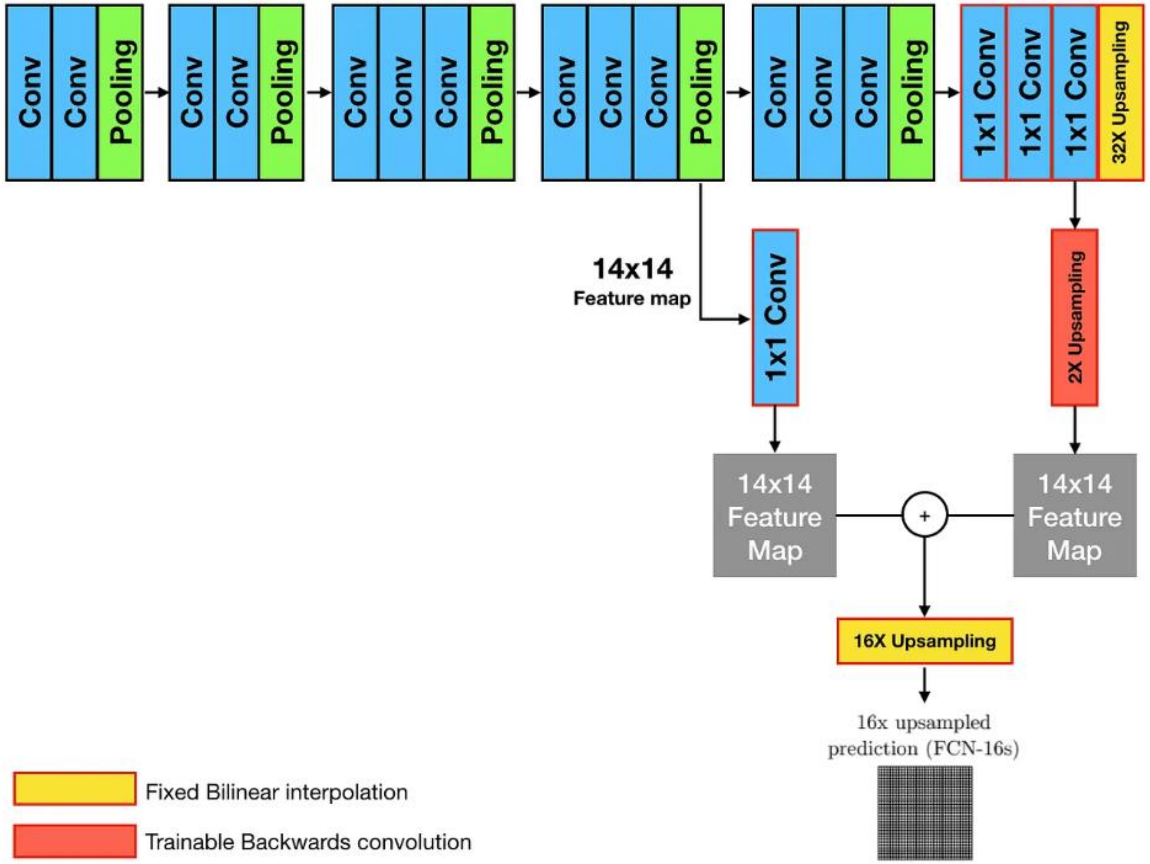


Skip Architecture

- **Skip Architecture for Better Segmentation**
  - Architecture variants

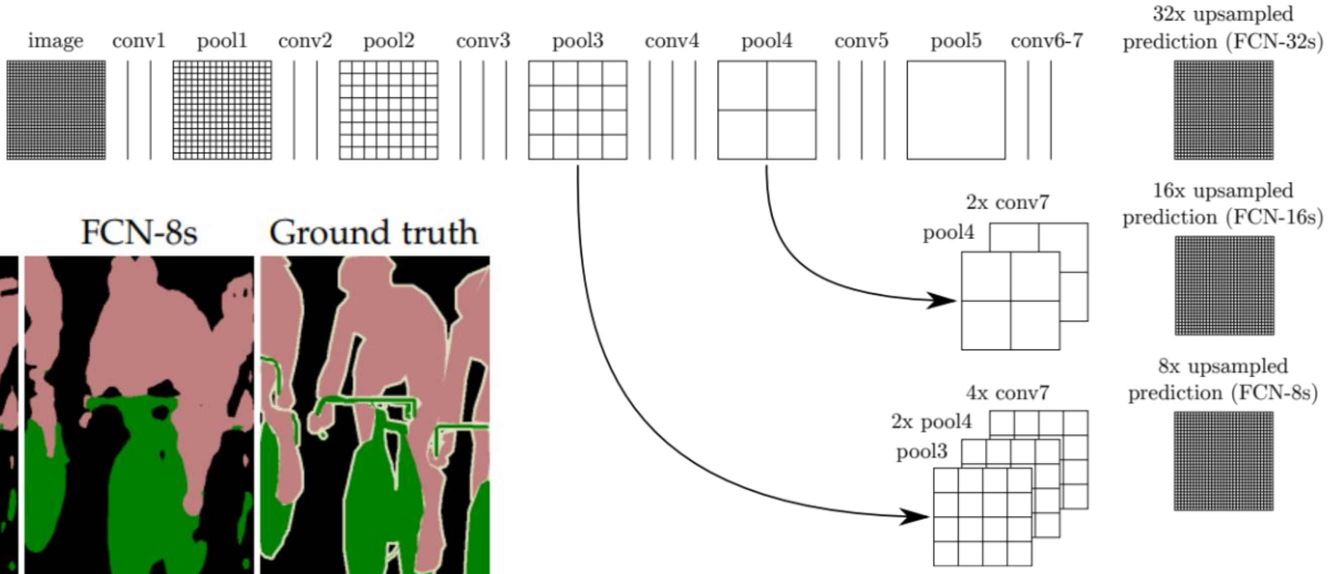


FCN-8s: Final + pool4 + pool3 (stride 8) — most detailed boundaries.

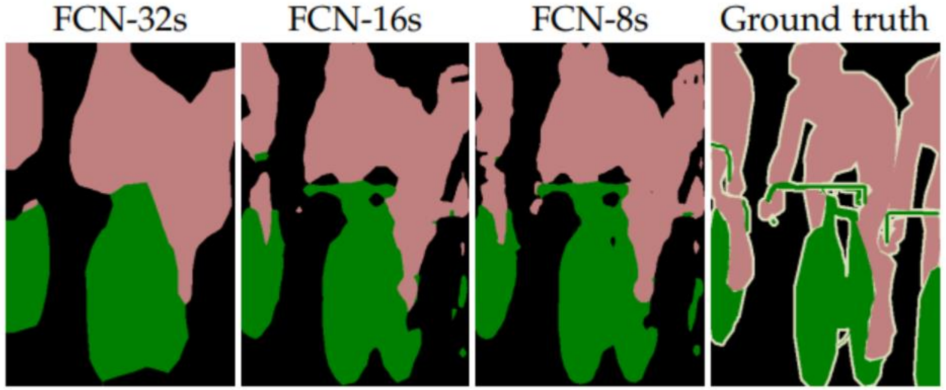


FCN-16s: Final + pool4 layer (stride 16) — better boundaries.

FCN Results and Key Takeaways



- **FCN Performance Highlights**
  - **Performance Trend**



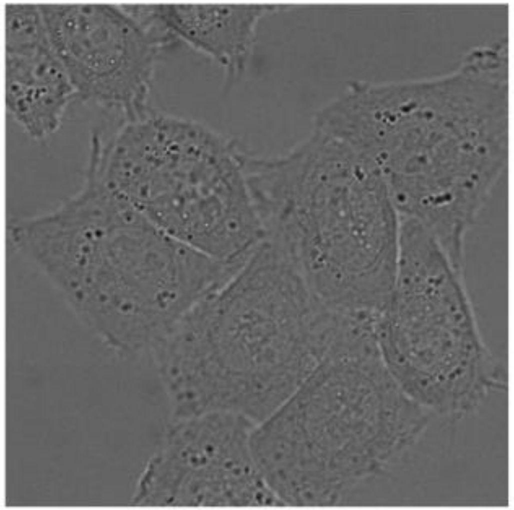
    - **FCN-32s → FCN-16s → FCN-8s**: Steady improvement in segmentation accuracy.
    - Finer strides capture more precise object boundaries.
  - **Quantitative Impact**
    - Significant mean IU improvement over prior state-of-the-art.
    - ~20% relative gain on benchmarks such as **PASCAL VOC 2011/2012**, **NYUDv2**, and **SIFT Flow**.
  - **Legacy**
    - Provided the foundation for later architectures (U-Net, SegNet, DeepLab, etc.).

Introduction to U-Net

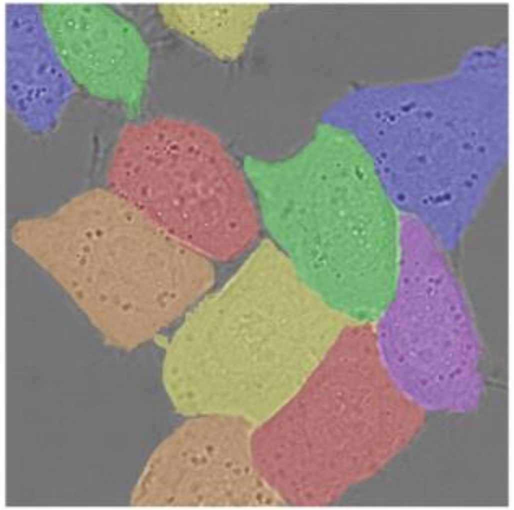
- **U-Net: Convolutional Networks for Biomedical Image Segmentation**
  - Published at **MICCAI 2015** by Olaf Ronneberger et al.
  - Designed for **biomedical image segmentation** with **limited training data**.
  - Key innovation: **U-shaped architecture** combining
    - **Contracting Path** → capture context
    - **Expansive Path** → enable precise localization
  - Outperformed previous state-of-the-art on ISBI 2015 challenges.

Motivation – U-Net

- **Why U-Net?**
  - **1. Problem in Biomedical Segmentation**
    - Small, annotated datasets
    - Need for **pixel-level** classification (semantic segmentation)
    - Critical to preserve both
      - ✓ **Context**
        - ➢ Global semantic understanding (what is in the image)
      - ✓ **Localization**
        - ➢ Precise spatial boundaries (where the object is)



Biomedical Image

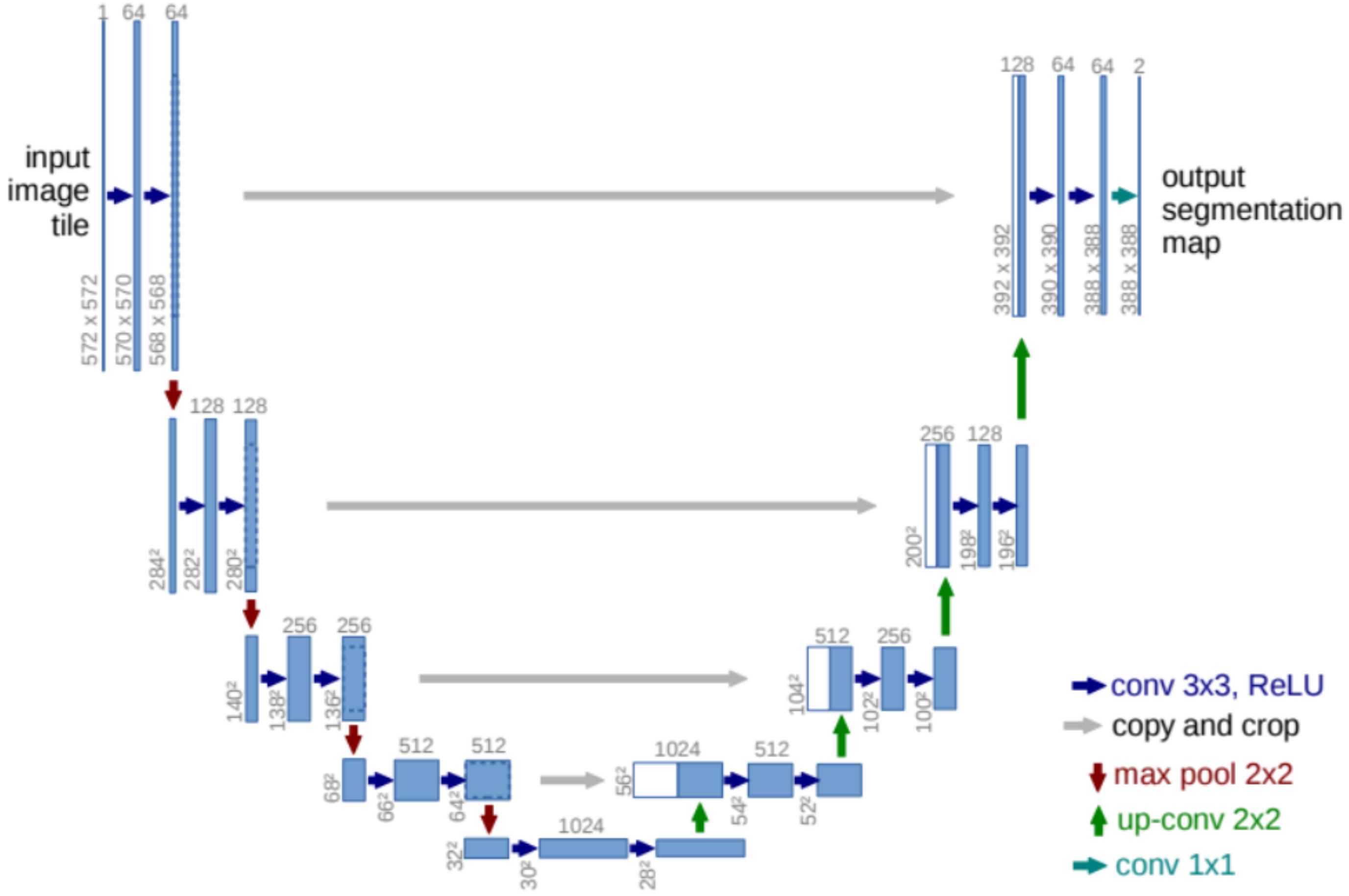


Ground-truth (Label)

  - **2. Limitations of Sliding-Window CNNs (Patch-Based Methods)**
    - **Inefficient computation**: neighboring patches overlap heavily → redundant convolution operations.
    - **Context–Localization trade-off**
      - ✓ Large patch → captures context but loses fine detail.
      - ✓ Small patch → keeps detail but misses context.
    - Cannot leverage **shared computation** across overlapping regions.

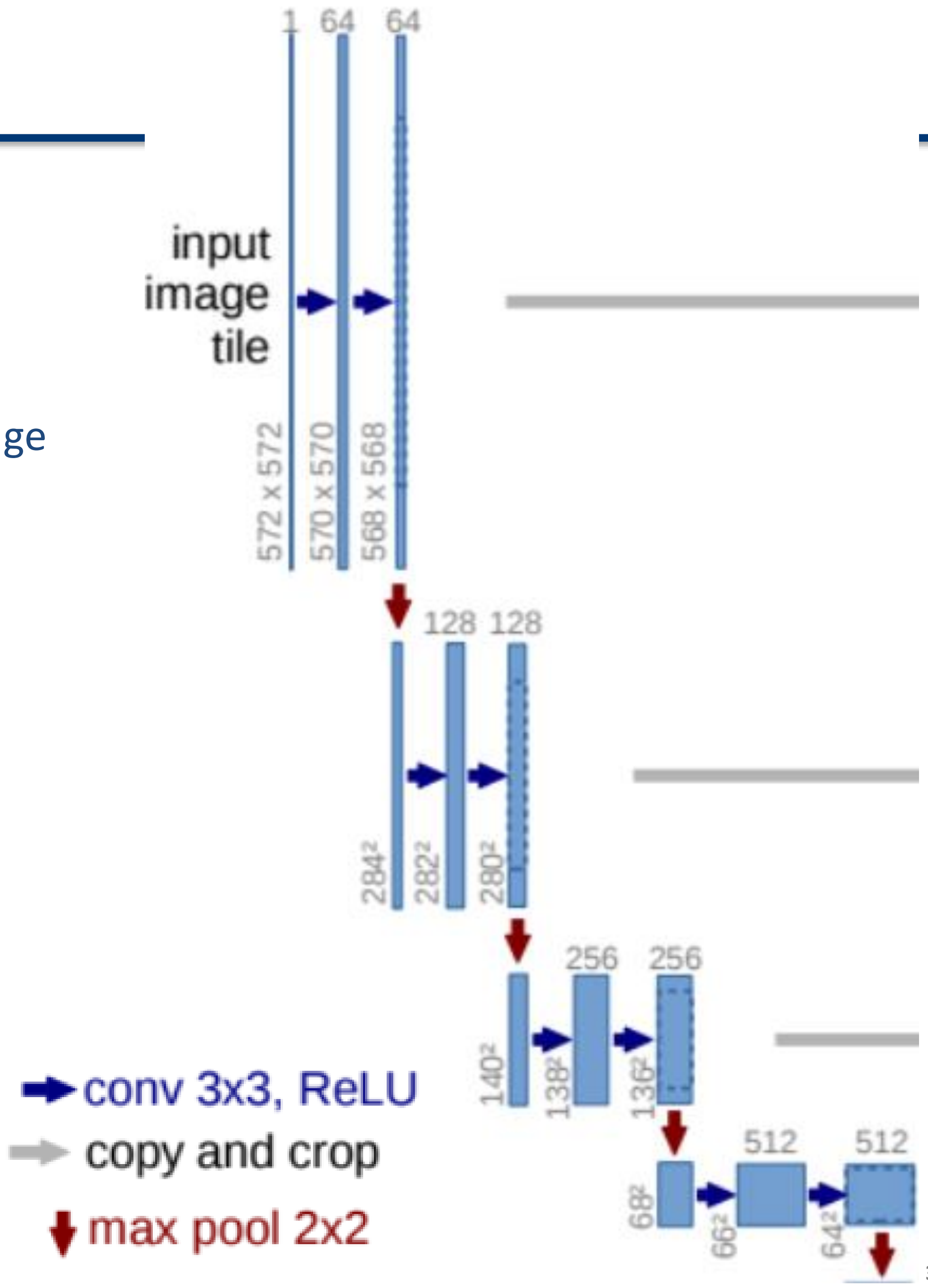
Motivation – U-Net

- **Why U-Net?**
  - **3. U-Net's Approach**
    - **(1) Fully Convolutional**
      - ✓Process the whole image at once.
    - **(2) Encoder–Decoder Structure**
      - ✓Encoder (contracting path) captures context.
      - ✓Decoder (expansive path) restores spatial resolution.
    - **(3) Skip Connections**
      - ✓Combine fine detail from early layers with deep semantic info.
      - ✓Designed to work **efficiently with small biomedical datasets**.



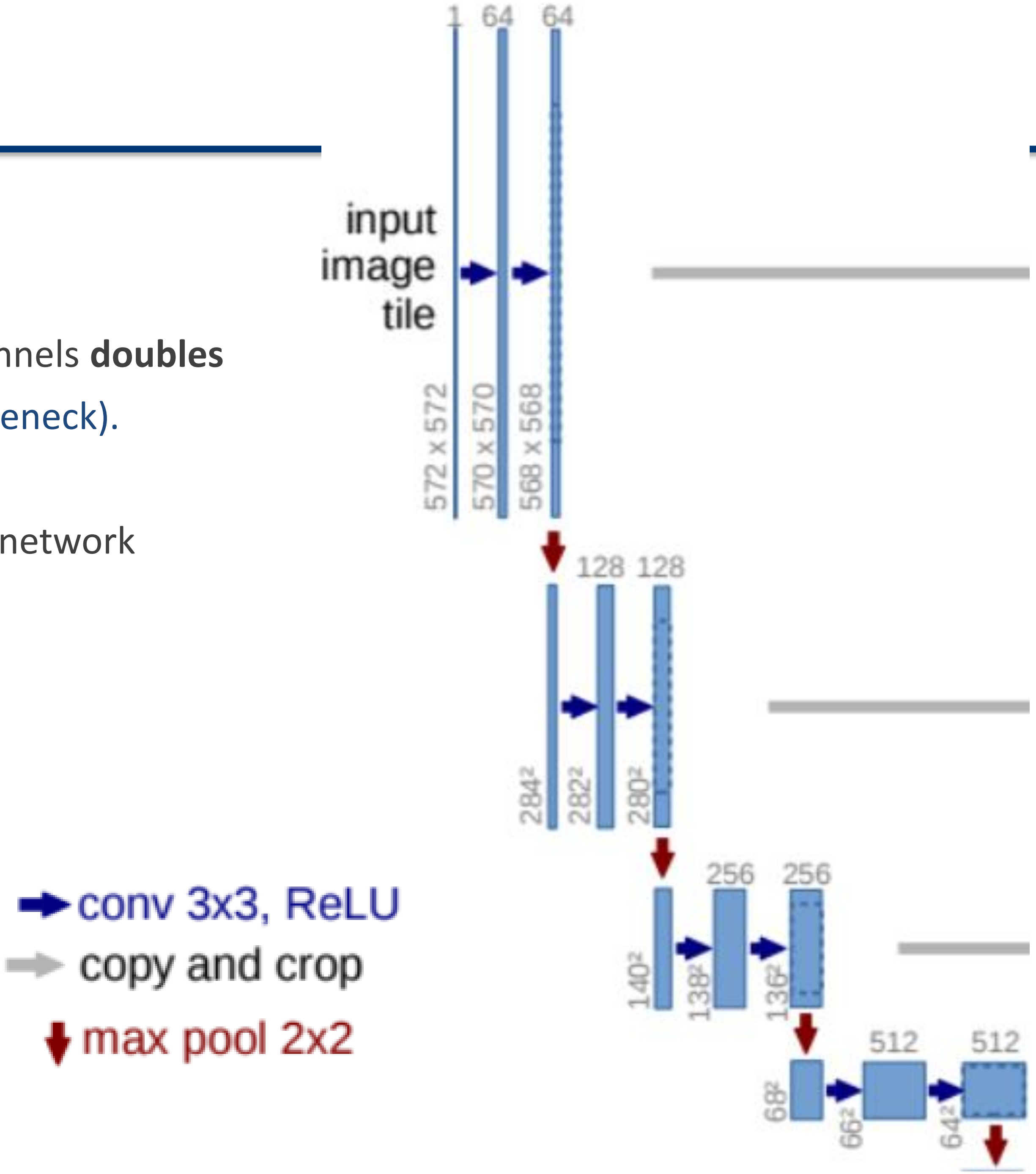
Architecture Overview

- **The U-Shaped Architecture**
  - **1. Contracting Path (Encoder)**
    - **Purpose**
      - ✓**Capture context** by progressively downsampling the input image while increasing the number of feature channels.
    - **Structure per Downsampling Step**
      - ✓**Step 1. 3×3 Convolution** (stride=1, **valid padding**) → ReLU → *(optional) BatchNorm*
        - ➢No padding → feature map shrinks by 2 pixels per conv in each spatial dimension.
      - ✓**Step 2. 3×3 Convolution** (stride=1, valid padding) → ReLU → *(optional) BatchNorm*
      - ✓**Step 3. 2×2 Max Pooling** (stride=2) for downsampling.



Architecture Overview

- **The U-Shaped Architecture**
  - **1. Contracting Path (Encoder)**
    - After **each** downsampling step, the number of channels **doubles**
      - ✓E.g., 1 → 64 → 128 → 256 → 512 → 1024 (bottleneck).
    - Pooling **increases the receptive field**, allowing the network to capture more context from the input image.



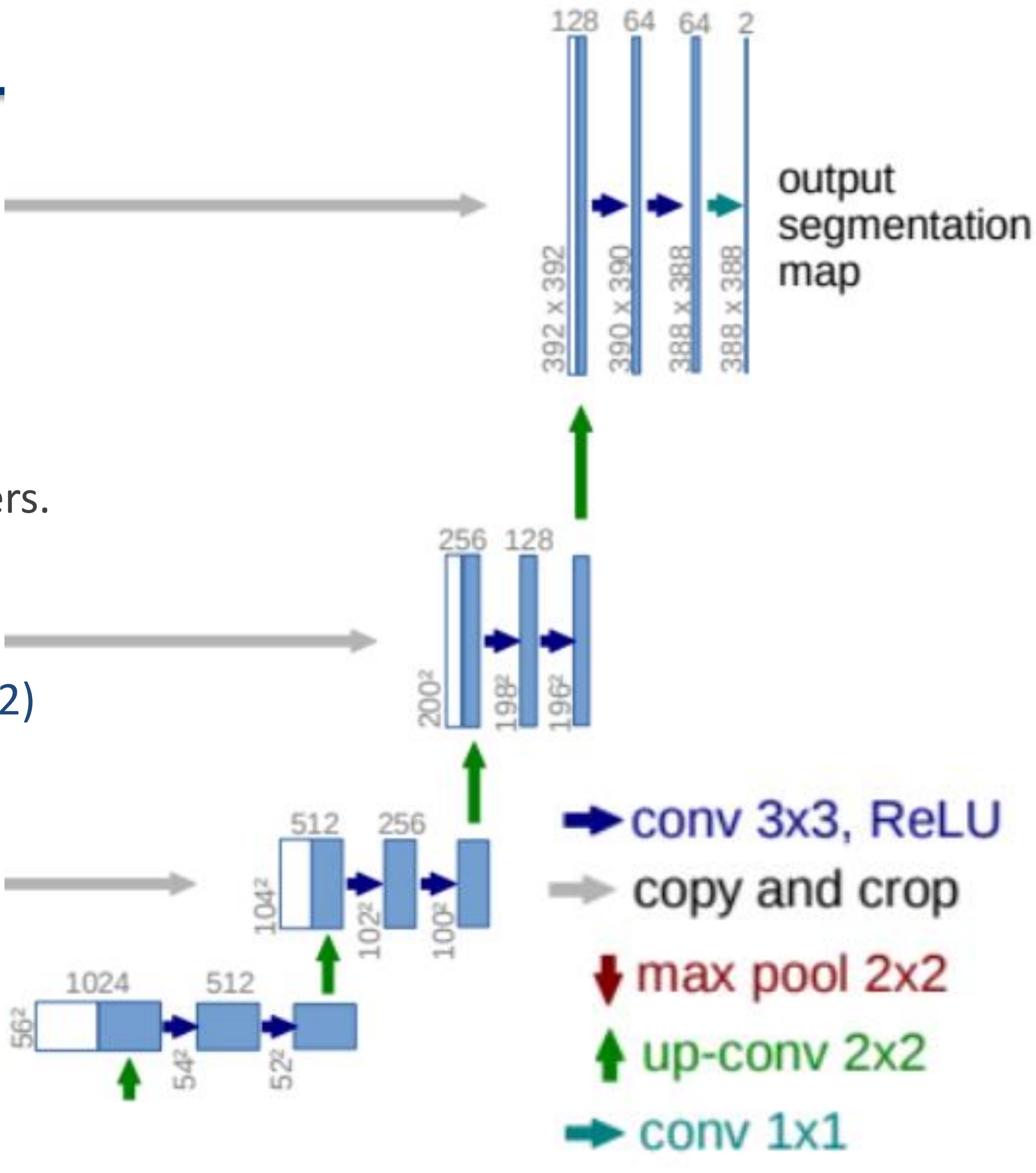
Architecture Overview

- **The U-Shaped Architecture**
  - **2. Bottleneck**
    - **Purpose**
      - ✓**Bridge between encoder and decoder**, containing the most abstract representation of the input.
    - **Structure**

      - ✓**3×3 Convolution** (stride=1, valid padding) → ReLU → *(optional) BatchNorm*
      - ✓**3×3 Convolution** (stride=1, valid padding) → ReLU → *(optional) BatchNorm*
    - **Dropout Layer** (optional in modern versions; not in original)
      - ✓Helps prevent overfitting and improves robustness to noise.
    - This layer has the **highest channel count** and smallest spatial resolution.

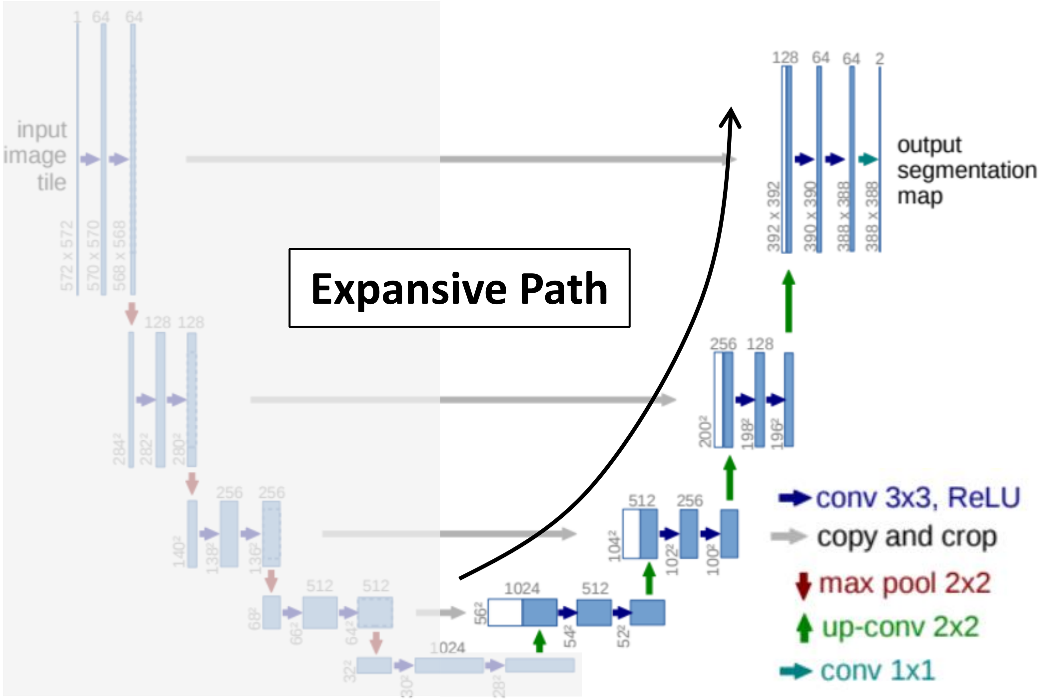
Architecture Overview

- **The U-Shaped Architecture**
  - **3. Expansive Path (Decoder)**
    - **Purpose**
      - ✓**Recover spatial resolution** and produce dense
        - ➢Pixel-level predictions by combining **contextual features** from the encoder with **localization features** from early layers.
    - **Structure per Upsampling Step**
      - ✓**Step 1. 2×2 Transposed Convolution (Deconvolution)** (stride=2)
        - ➢Upsamples the feature map by a factor of 2.
        - ➢Halves the number of channels.
      - ✓**Step 2. Crop & Concatenate**
        - ➢Take the corresponding feature map from the encoder (same depth level).
        - ➢Because of **no padding** in 3×3 convolutions, encoder feature maps are slightly smaller → **crop** to match dimensions before concatenation.



Architecture Overview

- **The U-Shaped Architecture**
  - **3. Expansive Path (Decoder)**



○ **Purpose**

✓**Recover spatial resolution** and produce dense

➢Pixel-level predictions by combining **contextual features** from the encoder with **localization features** from early layers.

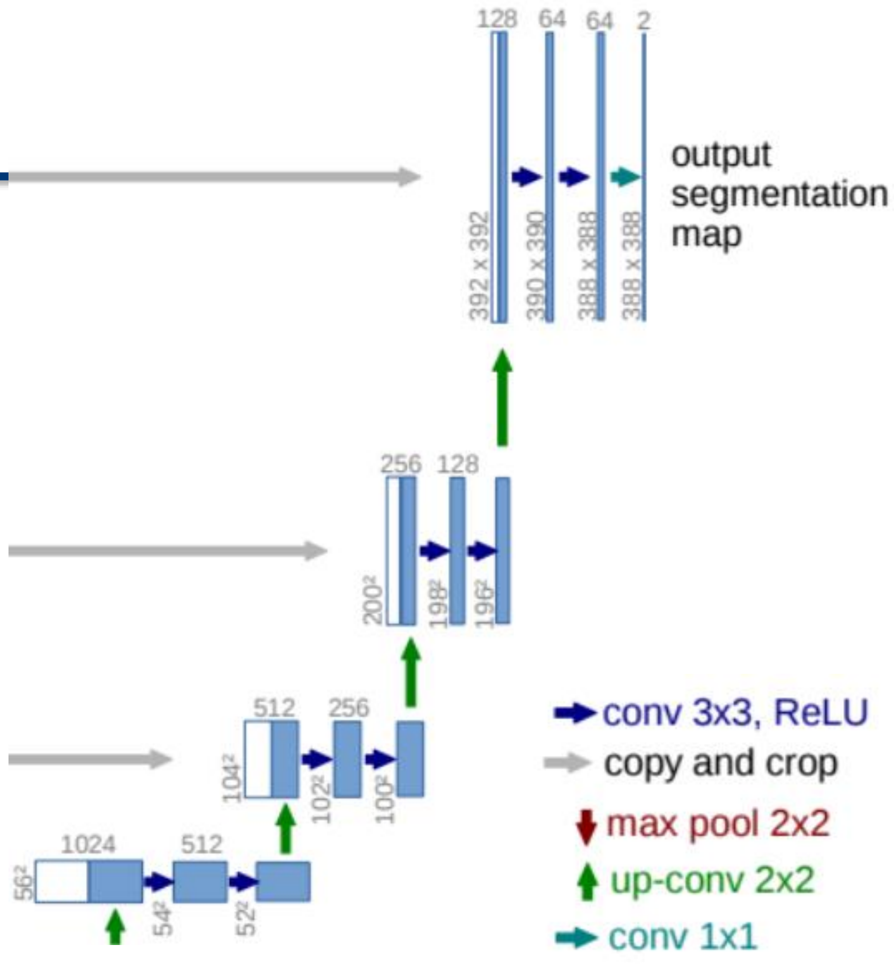
Architecture Overview

- **The U-Shaped Architecture**
  - **3. Expansive Path (Decoder)**
    - **Structure per Upsampling Step**

✓**Step 1. 2×2 Transposed Convolution (Deconvolution)** (stride=2)

➢Upsamples the feature map by a factor of 2.

➢Halves the number of channels.



✓**Step 2. Crop & Concatenate**

➢Take the corresponding feature map from the encoder (same depth level).

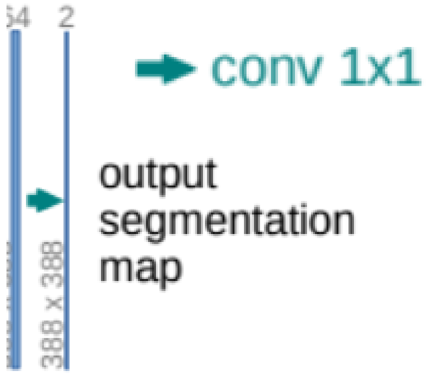
➢Because of **no padding** in 3×3 convolutions,
encoder feature maps are slightly smaller → **crop** to match dimensions before concatenation.

✓**Step 3. 3×3 Convolution** (stride=1, valid padding) → ReLU → *(optional) BatchNorm*

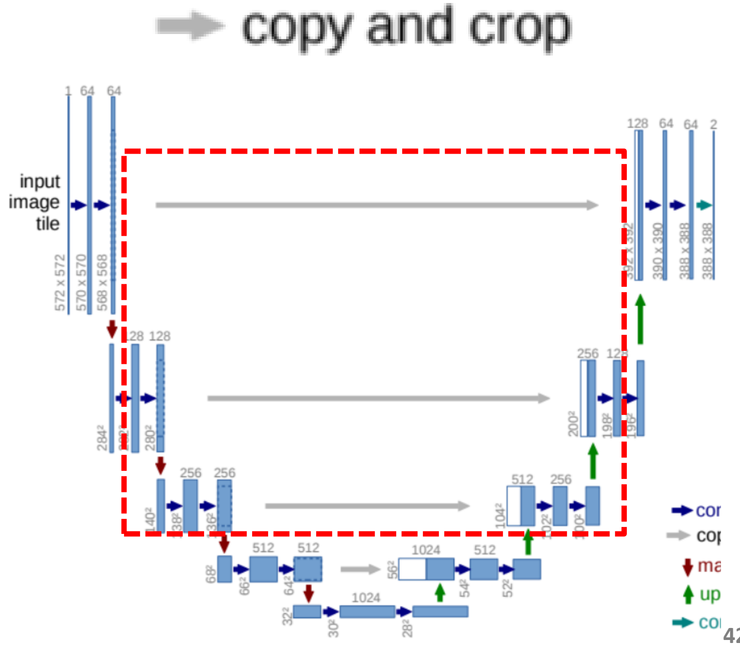
✓**Step 4. 3×3 Convolution** (stride=1, valid padding) → ReLU → *(optional) BatchNorm*

Architecture Overview

- **The U-Shaped Architecture**
  - **4. Output Layer**
    - o **1×1 Convolution** with **C filters**, where *C* = number of segmentation classes.
    - o Produces a **(H × W × C)** score map, where each pixel has a vector of class probabilities.

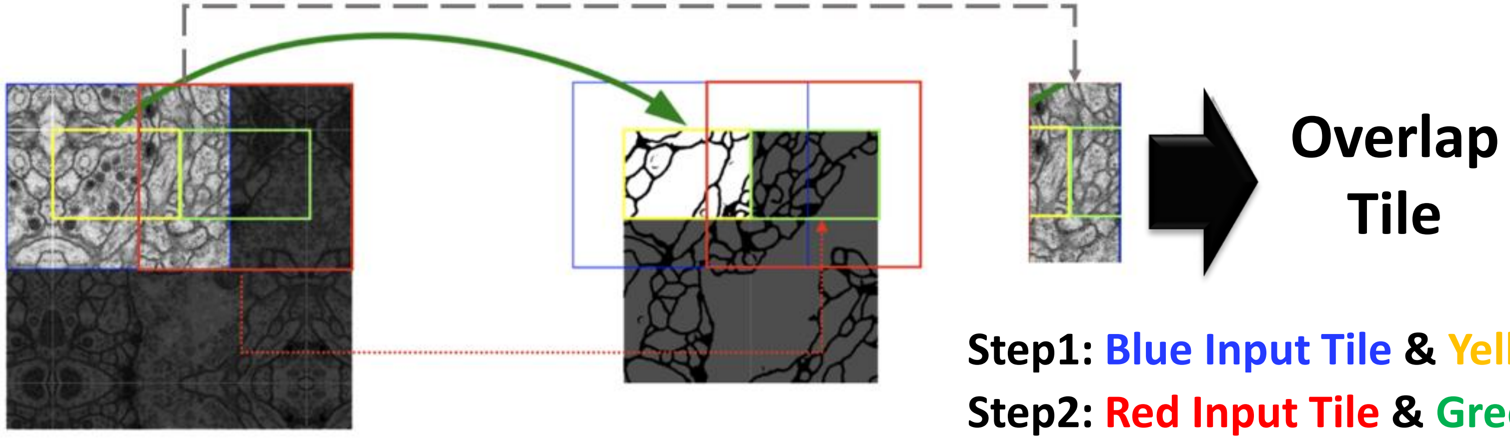


  - **5. Skip Connections**
    - o **Purpose**
      - ✓Preserving Spatial Detail with Skip Connections
      - ✓**Without skips**
        - ➢decoder relies solely on deep, coarse features → blurry outputs.
      - ✓**With skips** – combine
        - ➢**Low-level appearance features** (from early layers)
        - ➢**High-level semantic features** (from deep layers)
    - o Requires **crop & copy** due to valid convolutions reducing feature map size.



Training Strategies in U-Net

- **Key Training Strategies for High-Quality Segmentation**
  - **Strategy 1. Overlap-Tile Strategy**
    - **Purpose:** Handle large images and ensure predictions are accurate at boundaries.

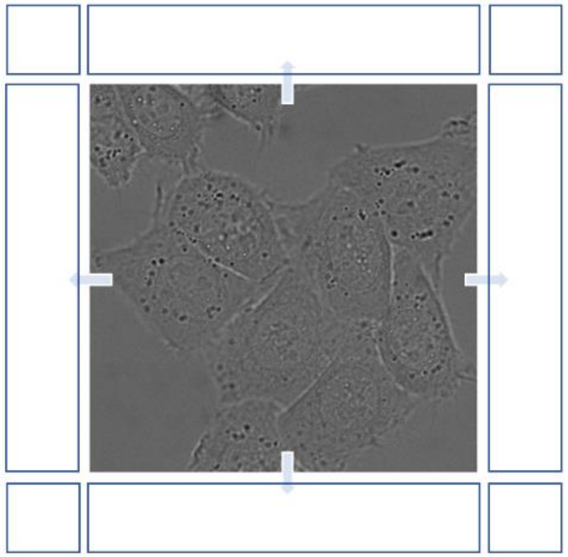


Step1: Blue Input Tile & Yellow Output Tile
Step2: Red Input Tile & Green Output Tile

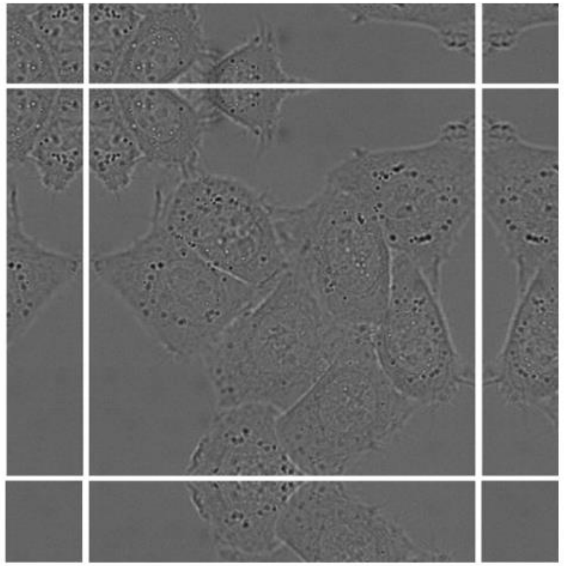
    - **How it works**
      - ✓Split large input images into smaller tiles with overlapping regions.
      - ✓Each tile is fed into the network, producing a smaller output region due to valid padding in convolutions.
      - ✓Overlap ensures full coverage and avoids loss of context at the borders.
    - **Key Benefit**
      - ✓Maintains context for edge regions and prevents border artifacts.

Training Strategies in U-Net

- **Key Training Strategies for High-Quality Segmentation**
  - **Strategy 2. Mirroring Extrapolation**
    - **Purpose:** Provide meaningful context for border pixels without introducing artificial padding values.
    - **How it works**
      - ✓Extend the input image by mirroring its borders.
      - ✓This mirrored extension surrounds the original image before tiling.
    - **Why it's useful in biomedical images**
      - ✓Many biological structures (e.g., cells) have symmetrical patterns.
      - ✓Mirroring preserves realistic textures at the borders, helping the network learn better boundary representations.



Origin Image

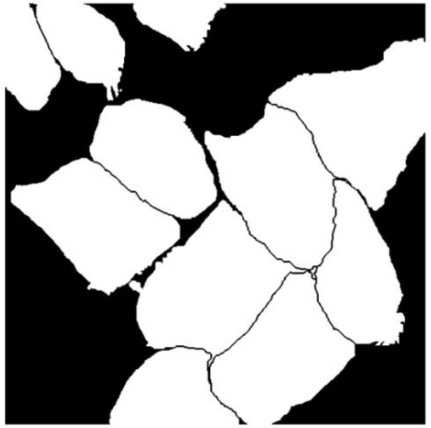


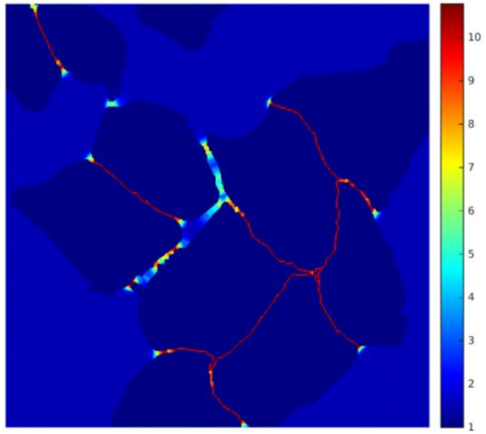
After Mirroring

Training Strategies in U-Net

- **Key Training Strategies for High-Quality Segmentation**
  - **Strategy 3. Weighted Loss for Boundary Separation**
    - o **Purpose:** Improve segmentation in regions where objects touch or have thin boundaries.
    - o **How it works**

Segmented Image





Visualized Weight Map

✓Compute a **weight map** from ground truth

➢Higher weights near boundaries between touching objects.

➢Lower weights elsewhere.

✓Use this weight map in the pixel-wise cross-entropy loss to emphasize difficult boundary pixels.

o **Effect**

✓The network learns to focus on separating closely packed or touching objects.

Summary & Key Takeaways

- **FCN & U-Net: Foundations of Modern Segmentation**
  - **1. FCN (Fully Convolutional Network)**
    - **Key Idea:** Replace fully connected layers with convolution layers → accept arbitrary input size.
    - **Upsampling:** Learnable deconvolution layers (backwards convolution) to restore resolution.
    - **Skip Architecture:** Combines deep semantic info with shallow spatial info for sharper boundaries (FCN-32s → FCN-16s → FCN-8s).
    - **Impact:** First end-to-end trainable CNN for dense prediction; influenced most later segmentation models.
  - **2. U-Net**
    - **Architecture:** Symmetric **U-shape** with **Contracting Path** (context) and **Expansive Path** (localization).
    - **Skip Connections:** Concatenate encoder features to decoder features at matching resolution for precise segmentation.
    - **Specialized Training Strategies:**
      - ✓**Overlap-Tile** for large images
      - ✓**Mirroring Extrapolation** for border pixels
      - ✓**Weighted Loss** to separate touching objects
    - **Impact:** State-of-the-art in biomedical segmentation, strong performance with limited data.

Summary & Key Takeaways

- **FCN & U-Net: Foundations of Modern Segmentation**
  - **3. Key Insights**
    - **Preserving spatial information** is crucial for pixel-wise tasks → skip connections are a common solution.
    - **Upsampling quality** directly affects boundary accuracy.
    - **Transfer learning** and **augmentation** help overcome limited labeled data.