

Day 3 (part 1): Computer Vision Summary

Note: Do Not depend entirely on this and study from the official slides.

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Image Segmentation

Task	Image classification	Image segmentation
• Goal	Identify the main/dominant object	Boundaries of all objects and background
• Output	Single label for the whole image	Pixel level map, every pixel gets a class
• Structure	Input image --> output single label (downsamples image into vector)	Input image --> output image (reserves dimension)
• Types		
1 - Semantic Segmentation	2 - Instance Segmentation	3- Panoptic Segmentation
<ul style="list-style-type: none">Label class categories only, doesn't distinguish between objectsExample: cats are colored blue, background red	<ul style="list-style-type: none">Distinguish separate instances of the same classExample: Cat 1 is blue cat 2 is red	<ul style="list-style-type: none">Semantic + instanceexample: color different instances plus including the background also

The Architecture Challenge

- Normal CNNs shrink images , while Segmentation needs the same HxW
 - **Problem:** pooling layers reduce spatial resolution. We loose the fine details and size needed for segmentation and doing standard CNNs with original image resolution will be very expensive
 - **Solution :** Use Encoder - Decoder Architecture
 - **Encoder (Downsampling):** Extract features (normal cnn architecture)
 - **Decoder (Upsampling):** Recovers spatial resolution to match input size (opposite of conv)

Upsampling techniques

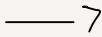
Method	Description	Learnable?
• Nearest Neighbor	Duplicate values to fill the larger grid	No
• Bed of nails	Place each value in specific place and fills the rest with zeros	No
• Max Unpooling	Smart memory: Remembers the index of the max value from the pooling step and puts the value back exactly to preserve spatial details	No
• Transpose Convolution	Gold Standard: A <u>reverse</u> convolution with learnable weights that learns how to optimally upsample	Yes 

- Nearest Neighbor

1		2	
3		4	

 2×2

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

 4×4


1	
2	
3	

 2×2

1	1	2	0
1	1	0	0
3	0	4	0
0	0	0	0

 4×4

- Bed of nails

1	2	6	3
3	5	2	1
1	2	2	1
7	3	4	8

 4×4

5	6
7	8

 2×2

- max pooling

1	2
3	4

 2×2

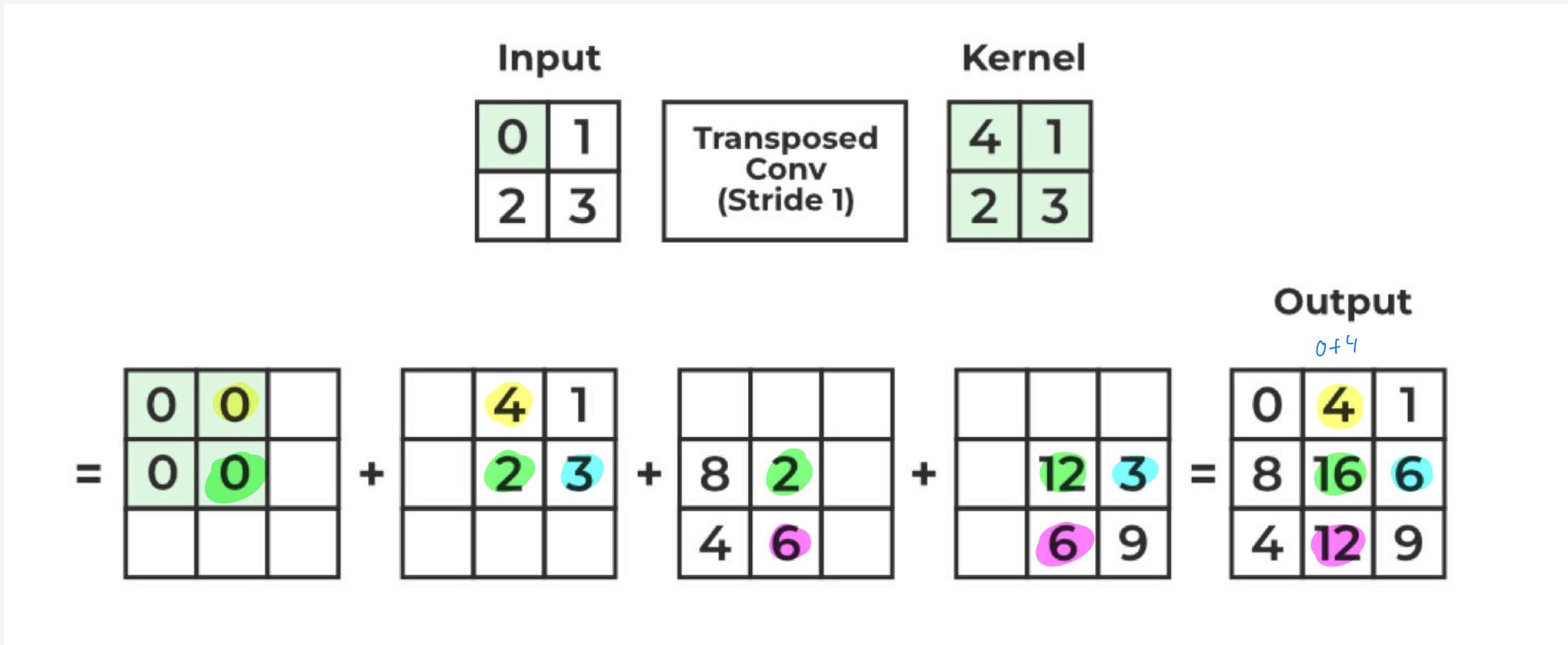
0	0	2	0
0	1	0	0
0	0	0	0
3	0	0	4

 4×4

- Max Unpooling

Transposed Convolution (Learnable upsampling)

- The 'opposite' of Normal Convolution
 - **Concept** : Instead of shrinking the image (downsample), it grows the image (upsampling) using learnable weights.
 - Normal Conv. : put kernel on **INPUT** - - -> Do dot product - - -> get 1 output (many to one)
 - Transposed Conv. : put kernel on **OUTPUT** - - -> use input as scaler - - -> copy the scaled kernel to output (one to many)
 - **The Mechanism**: Each pixel in the input act as a multiplier. It scales the entire kernel, and we stamp that scaled kernel onto the output feature map. Overlapping stamps are summed up



U-Net Architecture

- Problem: Important details and spatial information may be lost during DownSampling

 └ Solution (U-Net): Introduce Residual connections (skip connections) to preserve spatial information

 └ Directly connect features from DownSampling layers to upsampling layers as it helps to recover from lost spatial details and improve segmentation accuracy

- U Net structure: Encoder decoder shaped like U

- Left Side. : Standard CNN plus max pooling to capture context
- Right Side. : Transposed Conv to recover precise location

- Secret Recipe: Residuals (skip connections)

Skip connections from the DownSampling to the up sampling: high resolution feature maps from encoder to the corresponding layer in the decoder. The effect is that the decoder gets 'gps coordinates' spatial info from the encoder