Introduction to image segmentation

DEEP LEARNING FOR IMAGES WITH PYTORCH

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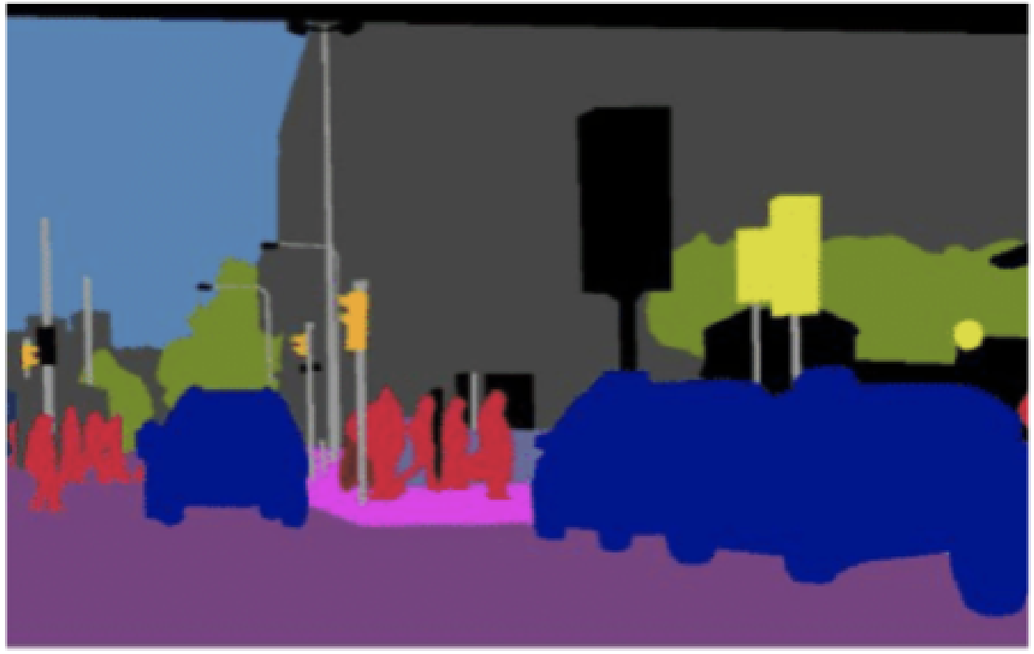
Image segmentation

- **Image segmentation** partitions the image into multiple segments on the pixel level
- Each pixel in an image is assigned to a particular segment
- Three types of segmentation:
  - Semantic segmentation
  - Instance segmentation
  - Panoptic segmentation

Semantic segmentation



- Each pixel classified into a class
- All pixels belonging to the same class are treated equally

Instance segmentation

- Distinguishes between different instances of the same class
- Background often not segmented

Panoptic segmentation

- Combines semantic and instance segmentations
- Assigns a unique label to each instance of an object
- Classifies background at pixel level

Data annotations

```
image = Image.open("images/British_Shorthair_36.jpg")
mask = Image.open("annots/British_Shorthair_36.png")

transform = transforms.Compose([
  transforms.ToTensor()
])
image_tensor = transform(image)
mask_tensor = transform(mask)

print(f"""Image shape: {image_tensor.shape}
          Mask shape: {mask_tensor.shape}""")
```

```
Image shape: torch.Size([3, 333, 500])
Mask shape: torch.Size([1, 333, 500])
```

Understanding the mask

- Dataset documentation:

  > Pixel Annotations: 1: Foreground 2: Background 3: Not classified

- Unique mask values:

```
mask_tensor.unique()
```

```
tensor([0.0039, 0.0078, 0.0118])
```

- Pixel values are divided by `255` :
  - `1 / 255 = 0.0039` - object
  - `2 / 255 = 0.0.0078` - background
  - `3 / 255 = 0.0118` - unclassified

Creating a binary mask

```
binary_mask = torch.where(
    mask_tensor == 1/255,
    torch.tensor(1.0),
    torch.tensor(0.0),
)

to_pil_image = transforms.ToPILImage()
mask = to_pil_image(binary_mask)
plt.imshow(mask)
```

- `torch.where()` :
  - Condition
  - Value to use if condition met
  - Value to use otherwise
- Transform mask to PIL image
- Display mask image

Segmenting the object

```
object_tensor = image_tensor * binary_mask

to_pil_image = transforms.ToPILImage()
object_image = to_pil_image(object_tensor)

plt.imshow(object_image)
```

- Multiply image with the binary mask
- Transform object to PIL image
- Display object image

Let's practice!

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Instance segmentation with Mask R-CNN

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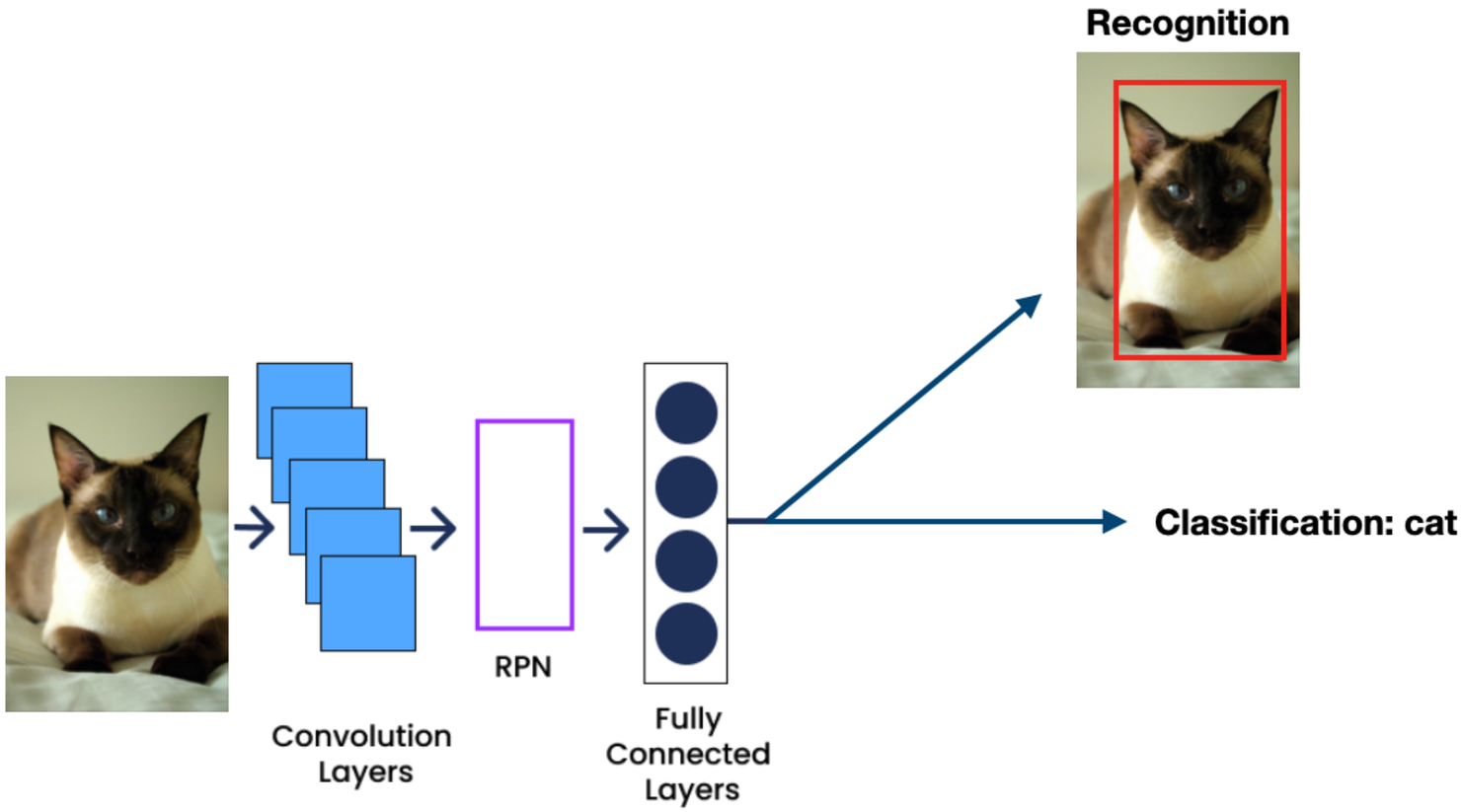
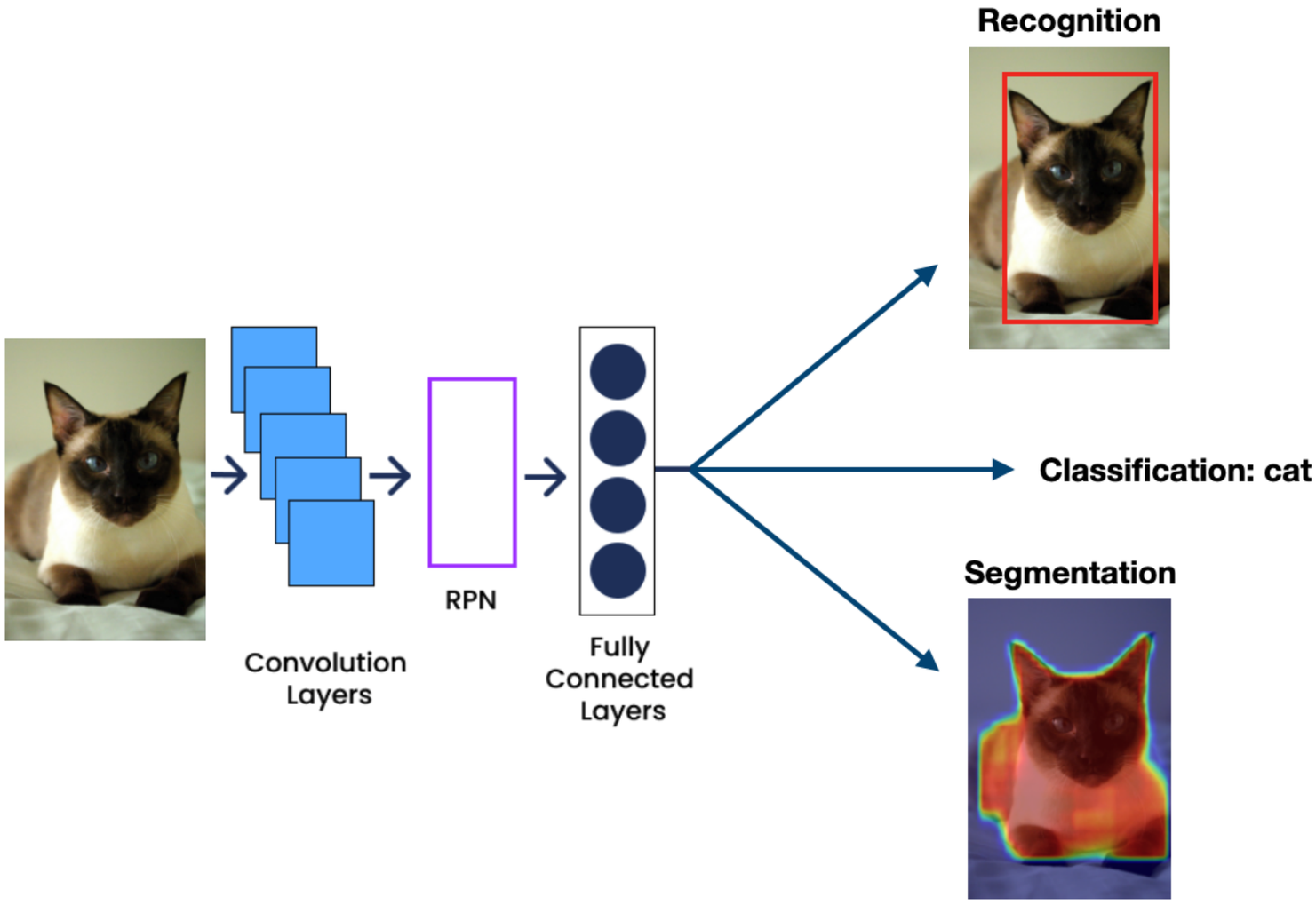
Faster R-CNN


Recognition
Classification: cat
RPN
Convolution Layers
Fully Connected Layers

Mask R-CNN


Recognition
Classification: cat
Segmentation
RPN
Convolution Layers
Fully Connected Layers

Pre-trained Masked R-CNN in PyTorch

```
from torchvision.models.detection import \
maskrcnn_resnet50_fpn

model = maskrcnn_resnet50_fpn(pretrained=True)
model.eval()

image = Image.open("cat_and_laptop.jpg")
transform = transforms.Compose([
    transforms.ToTensor()
])
image_tensor = transform(image).unsqueeze(0)

with torch.no_grad():
    prediction = model(image_tensor)
```

- Import the Mask R-CNN model
- Load pre-trained model
- Load test image and transform to tensor

- Pass image tensor to the model

Model outputs

- Labels

```
prediction[0]["labels"]
```

```
tensor([
    17, 73, 76, 73, 67, 42, 63, 84,73, 65,
    17, 73, 73, 73, 84, 72, 76, 76,17, 15
])
```

- Class names

```
print(class_names[17], class_names[73])
```

```
cat laptop
```

- Class probabilities

```
prediction[0]["scores"]
```

```
tensor([
    0.9981, 0.9672, 0.9061, 0.6893, 0.3729,
    ...,
    0.0745, 0.0705, 0.0623, 0.0610, 0.0508
])
```

- Masks

```
prediction[0]["masks"]
```

```
tensor([[[[0., 0., 0.,  ..., 0., 0., 0.],
          ...]]]])
```

Soft masks

- Unique mask values

```
prediction[0]["masks"].unique()
```

```
tensor([0.0000e+00, 5.9713e-08, ...,
        9.9989e-01, 9.9990e-01])
```

- Mask R-CNN masks:
  - Values between 0 and 1
  - Represent the model's confidence that each pixel belongs to the object
  - Provide more nuanced information than binary masks
  - Can be binarized by thresholding if needed

Displaying soft masks

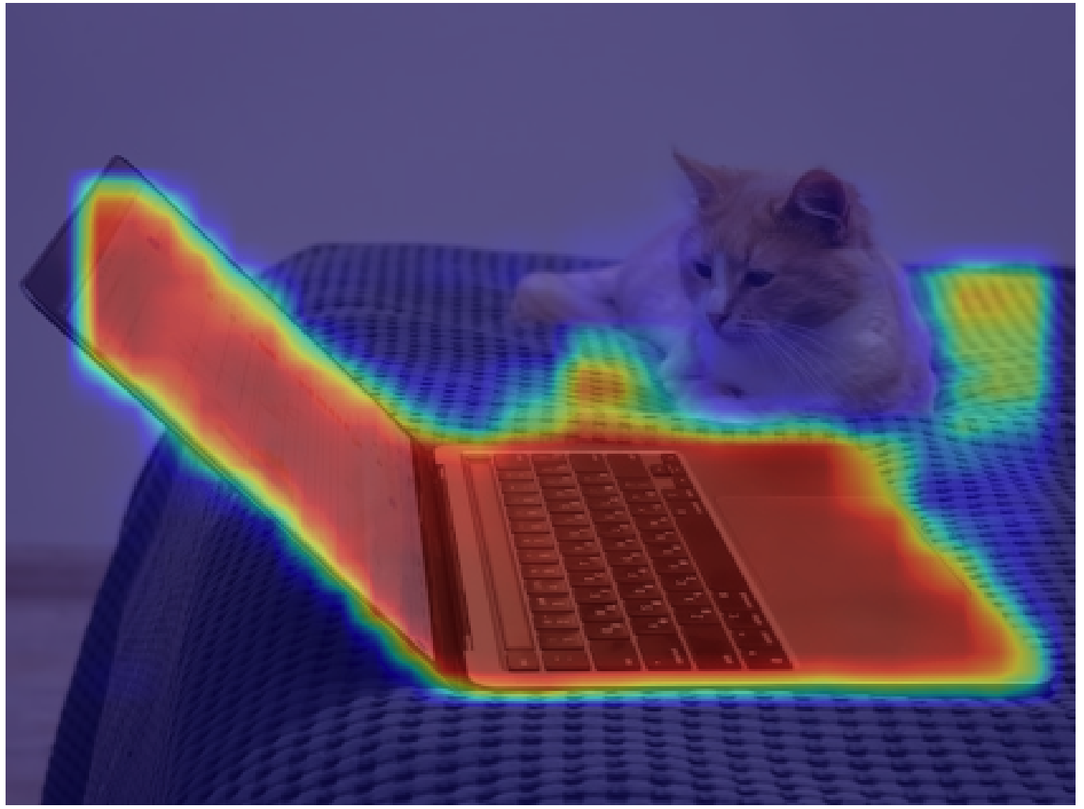
```
masks = prediction[0]["masks"]
labels = prediction[0]["labels"]

for i in range(2):
    plt.imshow(image)
    plt.imshow(
        masks[i, 0],
        cmap="jet",
        alpha=0.5,
    )
    plt.title(
        f"Object: {class_names[labels[i]]}"
    )
    plt.show()
```

- Extract masks and labels from prediction
- Iterate over top two objects, plotting the original image
- For each object, plot the semi-transparent mask
- Add title and display

Displaying soft masks

Object: cat

Object: laptop



Let's practice!

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Semantic segmentation with U-Net

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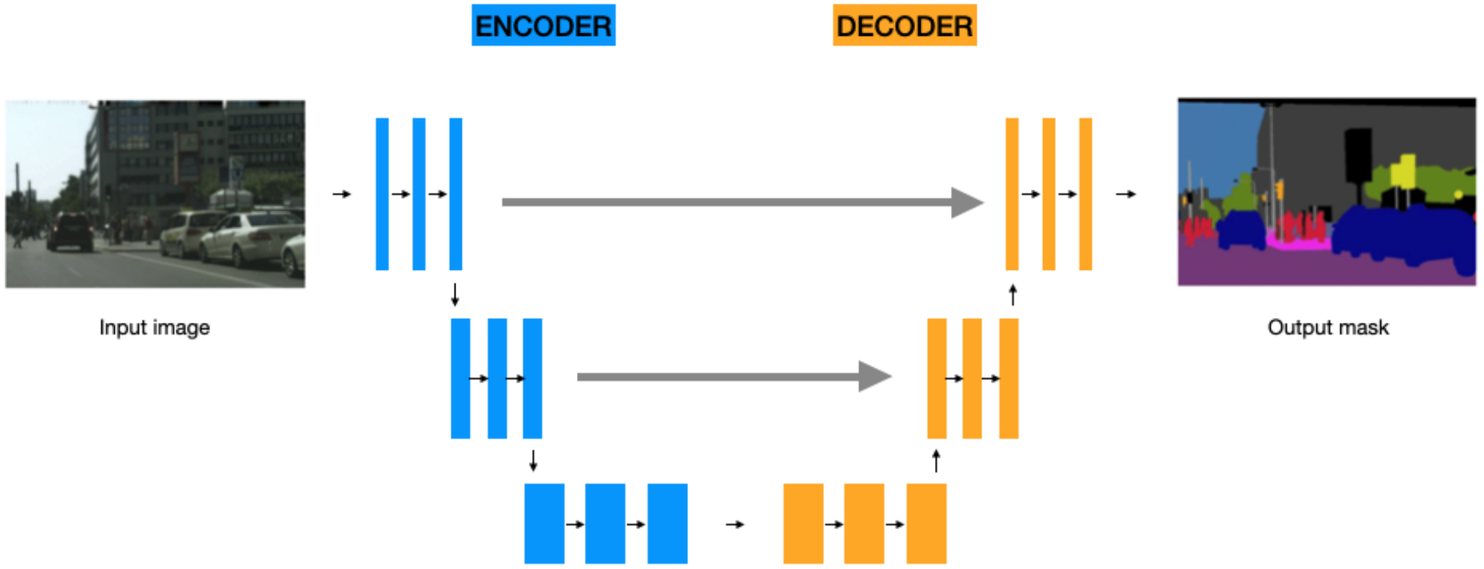
Semantic segmentation

- No distinction between different instances of the same class
- Useful for medical imaging or satellite image analysis
- Popular architecture: **U-Net**

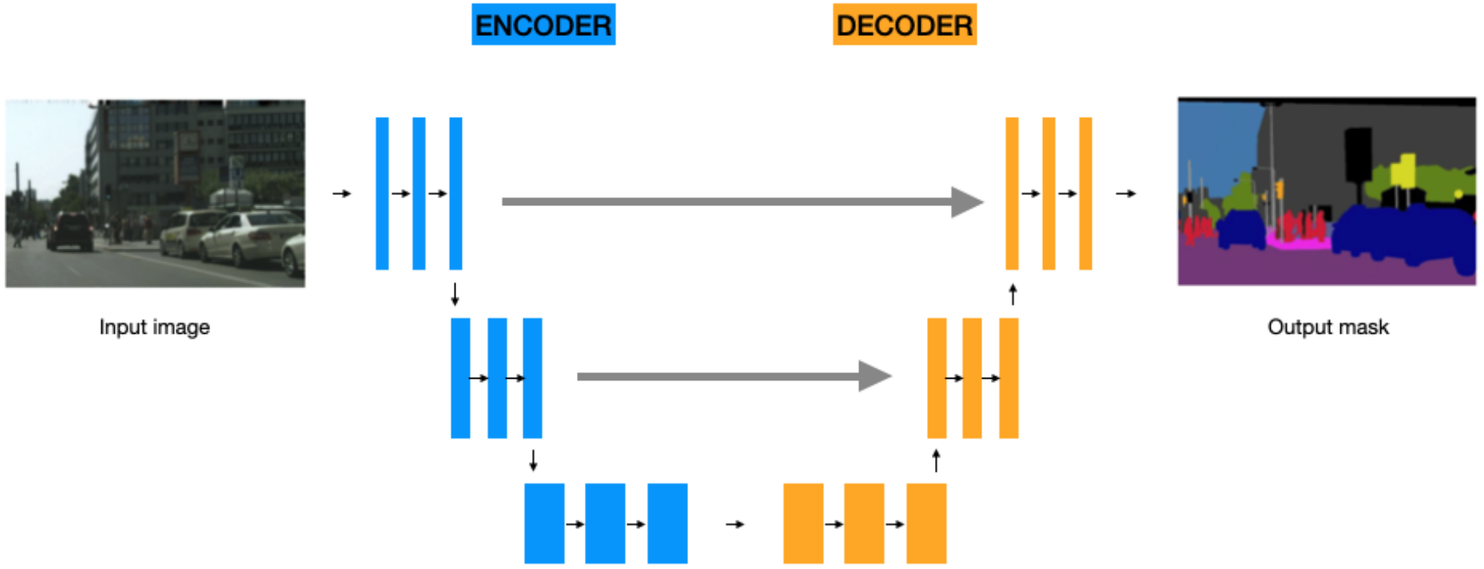
U-Net architecture



Encoder:

- Convolutional and pooling layers
- Downsampling: reduces spatial dimensions while increasing depth

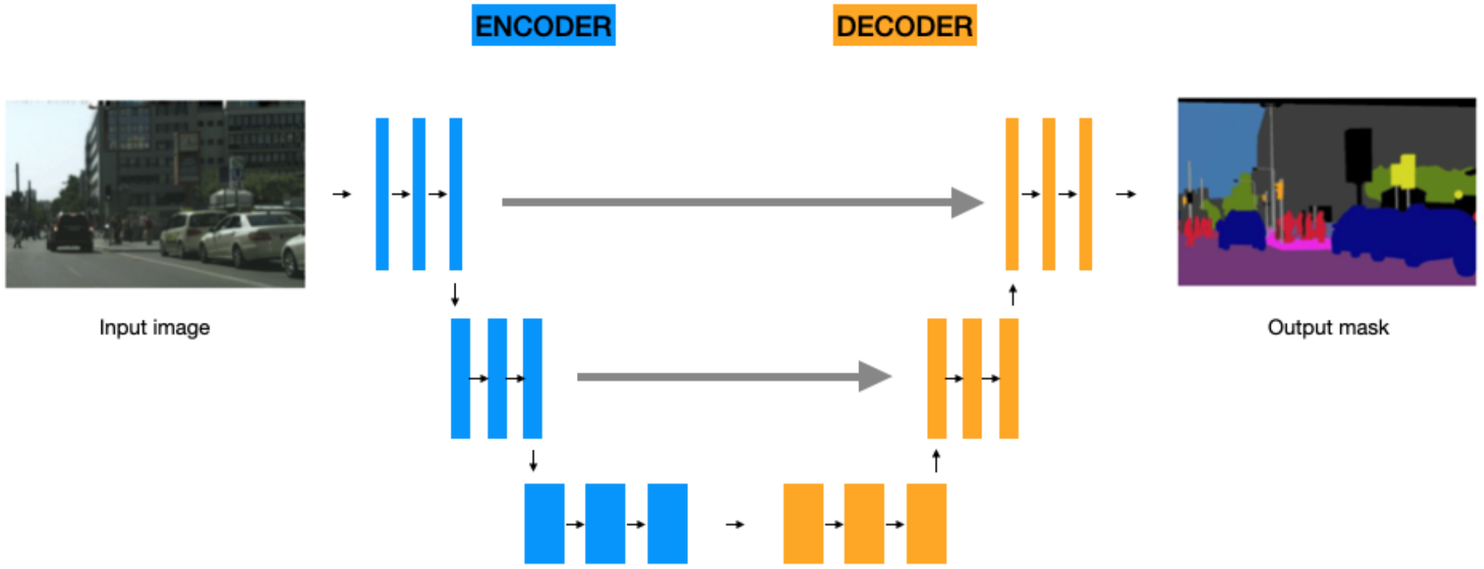
U-Net architecture



Decoder:

- Symmetric to the encoder
- Upsamples feature maps with transposed convolutions

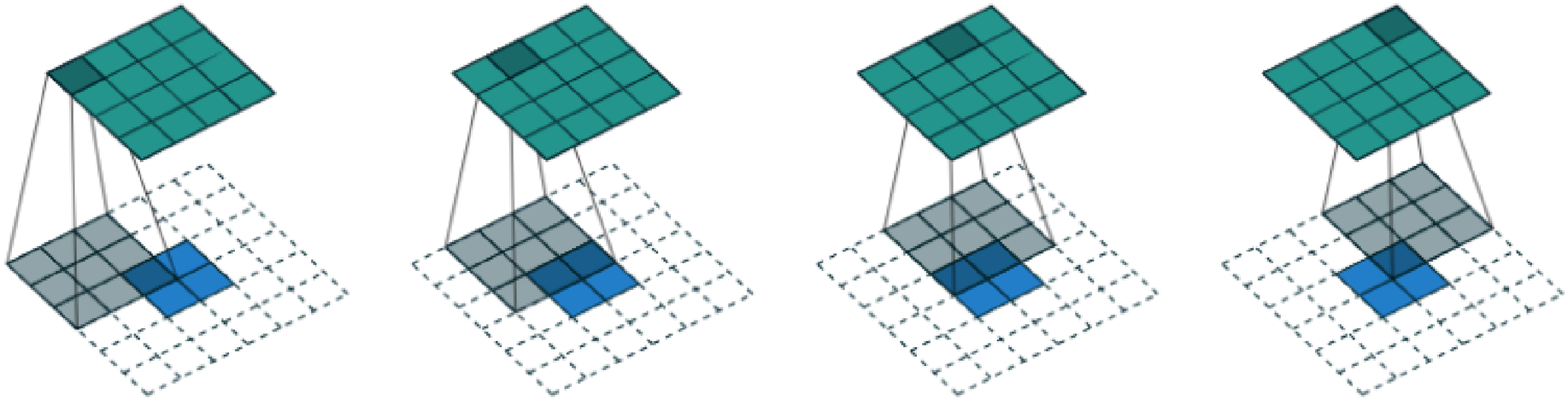
U-Net architecture



Skip connections:

- Links from the encoder to the decoder
- Preserve details lost in downsampling

Transposed convolution



- Upsamples feature maps in the decoder: increases height and width while reducing depth
- Transposed convolution process:
  1. Insert zeros between or around the input feature map
  2. Perform a regular convolution on the zero-padded input

Transposed convolution in PyTorch

```
import torch.nn as nn


upsample = nn.ConvTranspose2d(
    in_channels=in_channels,
    out_channels=out_channels,
    kernel_size=2,
    stride=2,
)
```

U-Net: layer definitions

```
class UNet(nn.Module):
    def __init__(self, in_channels, out_channels):
        super(UNet, self).__init__()

        self.enc1 = self.conv_block(in_channels, 64)
        self.enc2 = self.conv_block(64, 128)
        self.enc3 = self.conv_block(128, 256)
        self.enc4 = self.conv_block(256, 512)
        self.pool = nn.MaxPool2d(kernel_size=2, stride=2)

        self.upconv3 = nn.ConvTranspose2d(512, 256,
                                          kernel_size=2, stride=2)
        self.upconv2 = nn.ConvTranspose2d(256, 128,
                                          kernel_size=2, stride=2)
        self.upconv1 = nn.ConvTranspose2d(128, 64,
                                          kernel_size=2, stride=2)

        self.dec1 = self.conv_block(512, 256)
        self.dec2 = self.conv_block(256, 128)
        self.dec3 = self.conv_block(128, 64)
        self.out = nn.Conv2d(64, out_channels, kernel_size=1)
```

- Encoder:
  - Convolutional blocks

```
def conv_block(self, in_channels, out_channels):
return nn.Sequential(
  nn.Conv2d(in_channels, out_channels),
  nn.ReLU(inplace=True),
  nn.Conv2d(out_channels, out_channels),
  nn.ReLU(inplace=True)
)
```

  - Pooling layer
- Decoder:
  - Transposed convolutions
  - Convolutional blocks

U-Net: forward method

```
def forward(self, x):
    x1 = self.enc1(x)
    x2 = self.enc2(self.pool(x1))
    x3 = self.enc3(self.pool(x2))
    x4 = self.enc4(self.pool(x3))

    x = self.upconv3(x4)
    x = torch.cat([x, x3], dim=1)
    x = self.dec1(x)

    x = self.upconv2(x)
    x = torch.cat([x, x2], dim=1)
    x = self.dec2(x)

    x = self.upconv1(x)
    x = torch.cat([x, x1], dim=1)
    x = self.dec3(x)

    return self.out(x)
```

- Pass input through encoder's convolutional blocks and pooling layers
- Decoder and skip connections:
  - Pass encoded input through transpose convolution
  - Concatenate with corresponding encoder output
  - Pass through convolution block
  - Repeat for all decoder steps
- Return output of the last decoder step

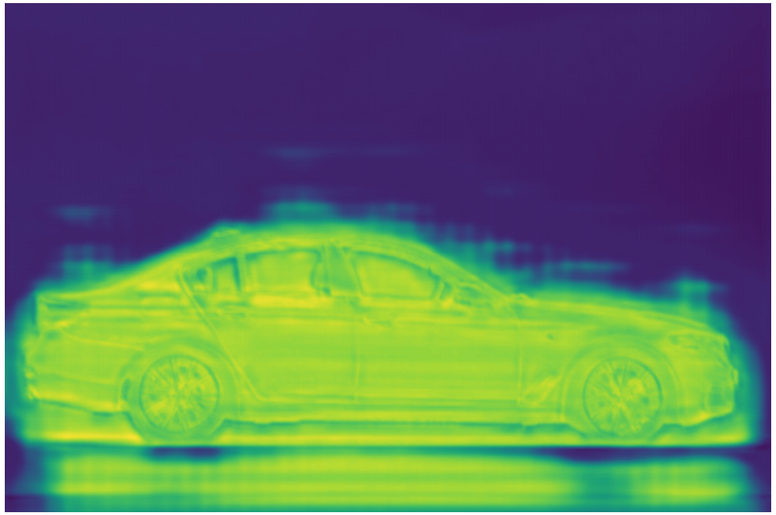
Running inference

```
model = UNet()
model.eval()

image = Image.open("car.jpg")
transform = transforms.Compose([transforms.ToTensor()])
image_tensor = transform(image).unsqueeze(0)

with torch.no_grad():
    prediction = model(image_tensor).squeeze(0)

plt.imshow(prediction[1, :, :])
plt.show()
```



Let's practice!

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Panoptic segmentation

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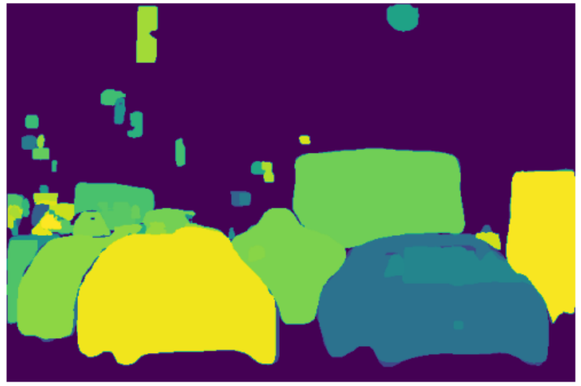
Panoptic segmentation challenge

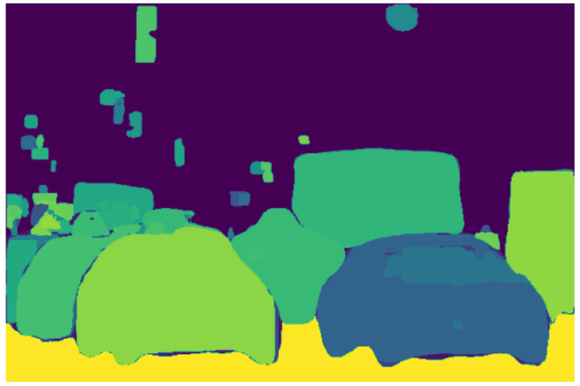
Original image

Semantic segmentation

Instance segmentation



Panoptic segmentation



Panoptic segmentation workflow

- Combining semantic and instance segmentation can be complex:
  - Overlaps
  - Ensuring unique instance IDs
- Our workflow:
  1. Generate semantic masks
  2. Combine them into a single mask
  3. Initialize the panoptic mask as the semantic mask
  4. Generate instance masks
  5. Iterate over instance masks and overlay detected objects onto the semantic mask

Semantic masks

```
model = UNet()

with torch.no_grad():
    semantic_masks = model(image_tensor)
    print(semantic_masks.shape)
```

```
torch.Size([1, 3, 427, 640])
```

```
semantic_mask = torch.argmax(
  semantic_masks, dim=1
)
```

- Instantiate the model
- Produce semantic masks for the input image
- Choose highest-probability class for each pixel

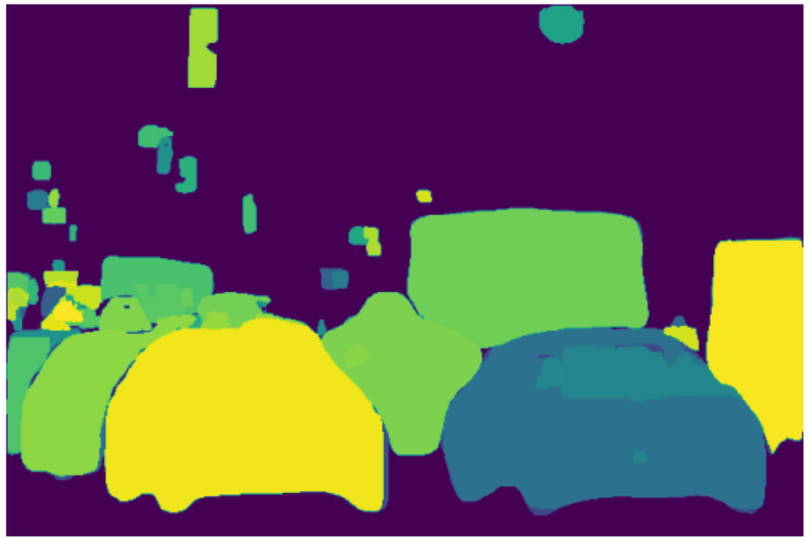
Instance masks

```
model = MaskRCNN()

with torch.no_grad():
    instance_masks = model(image_tensor)[0]["masks"]
    print(instance_masks.shape)
```

```
torch.Size([80, 1, 427, 640])
```

- Load instance segmentation model
- Produce instance masks

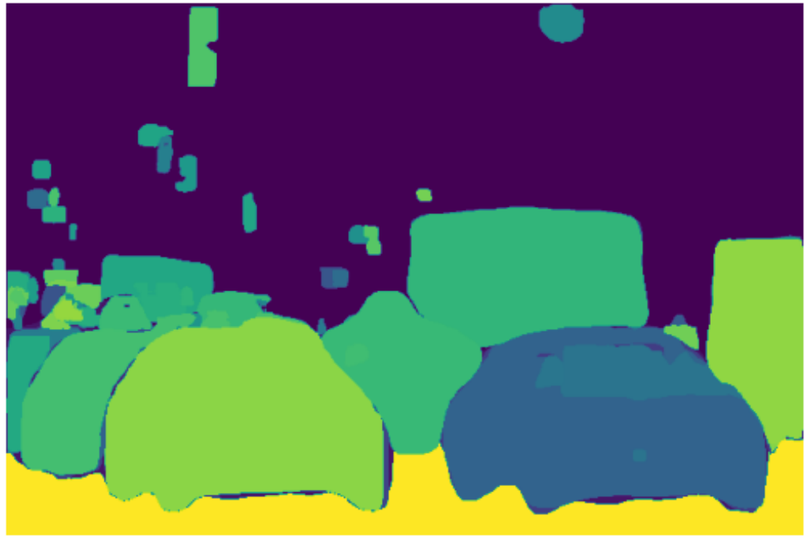


Panoptic masks

```
panoptic_mask = torch.clone(semantic_mask)

instance_id = 3
for mask in instance_masks:
    panoptic_mask[mask > 0.5] = instance_id
    instance_id += 1
```

- Initialize panoptic mask as semantic_mask
- Iterate over instance masks
- Set panoptic mask to instance ID where mask > 0.5
- Increase instance ID counter



Let's practice!

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