Segmentation Transformer: Object-Contextual Representations for Semantic Segmentation

📝 논문 저자 깃허브

HRNet-Semantic-Segmentation/seg_hrnet_ocr.py at HRNet-OCR · HRNet/HRNet-Semantic-Segmentation

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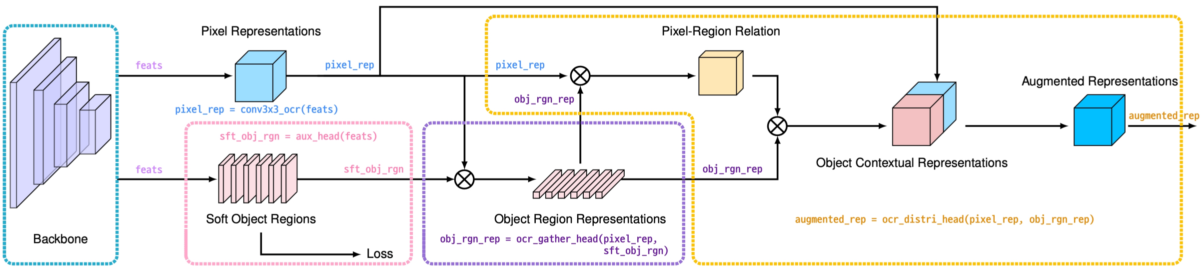
https://github.com/HRNet/HRNet-Semantic-Segmentation/blob/HRNet-OCR/lib/models/seg_hrnet_ocr.py

🔗 논문 링크

https://arxiv.org/pdf/1909.11065.pdf

목차

Segmentation Transformer - Code Implementation




```
def forward(self, x):
    # Input : torch.Size([1, 3, 1024, 2048])

    ...
    # (HRNet 코드)
    ...

    # Backbone output : torch.Size([1, 720, 256, 512])
    feats = torch.cat([x[0], x1, x2, x3], 1)

    # 1. Pixel Representations x_i : torch.Size([1, 512, 128, 256])
    pixel_rep = self.conv3x3_ocr(feats)

    # 2. Soft Object Regions(coarse seg map) M_K : torch.Size([1, 19, 128, 256])
    sft_obj_rgn = self.aux_head(feats)

    # 3. Object Region Representations f_k : torch.Size([1, 512, 19, 1])
    obj_rgn_rep = self.ocr_gather_head(feats=pixel_rep,
                                       probs=sft_obj_rgn)
```

```
# 4. Augmented Representations z_i : torch.Size([1, 512, 256, 512])
augmented_rep = self.ocr_distri_head(pixel_rep, obj_rgn_rep)

# 5. Final Segmentation Output : torch.Size([1, 19, 256, 512])
out = self.cls_head(augmented_rep)

# Backprop을 위한 output 2개
out_aux_seg = []
out_aux_seg.append(sft_obj_rgn) # Soft Object Regions(coarse seg map)
out_aux_seg.append(out)         # Final Segmentation Output

return out_aux_seg
```

1. Pixel Representations $\mathbf{x}_i$

[Code]

- `pixel_rep`

```
# 1. Pixel Representations x_i : torch.Size([1, 512, 128, 256])
pixel_rep = self.conv3x3_ocr(feats)
```

- `self.conv3x3_ocr`

```
self.conv3x3_ocr = nn.Sequential(
            nn.Conv2d(last_inp_channels, ocr_mid_channels,
                      kernel_size=3, stride=1, padding=1),
            BatchNorm2d(ocr_mid_channels),
            nn.ReLU(inplace=relu_inplace),
        )
```

[Concept]

- $\mathbf{x}_i$ is the representation of pixel p_i of an image I

2. Soft Object Regions M_K

[Code]

- `sft_obj_rgn`

```
# 2. Soft Object Regions(coarse seg map) M_K : torch.Size([1, 19, 128, 256])
sft_obj_rgn = self.aux_head(feats)
```

- `self.aux_head`

```
self.aux_head = nn.Sequential(
            nn.Conv2d(last_inp_channels, last_inp_channels,
                      kernel_size=1, stride=1, padding=0),
            BatchNorm2d(last_inp_channels),
            nn.ReLU(inplace=relu_inplace),
            nn.Conv2d(last_inp_channels, config.DATASET.NUM_CLA
SSES,
                      kernel_size=1, stride=1, padding=0, bias=
True)
        )
```

[Concept]

- We partition the image I into K soft object regions $\{M_1, M_2, \cdots, M_K\}$.
- Each object region M_K corresponds to the class k, and is represented by a 2D map (or coarse segmentation map), where each entry indicates the degree that the corresponding pixel belongs to the class k.

3. Object Region Representations $\mathbf{f}_k$

[Code]

- `obj_rgn_rep`

[Concept]

- We aggregate the representations of all the pixels weighted by their degrees belonging to the

```
# 3. Object Region Representations f_k : torch.Size([1, 512, 19, 1])
obj_rgn_rep = self.ocr_gather_head(feats=pixel_rep,
                                   probs=sft_obj_rgn)
```

▼ `self.ocr_gather_head`

```
self.ocr_gather_head = SpatialGather_Module(config.DATASET.NUM_CLASSES)
```

▼ `SpatialGather_Module`

```
class SpatialGather_Module(nn.Module):
    """
        Aggregate the context features according to the initial
        predicted probability distribution.
        Employ the soft-weighted method to aggregate the context.
    """
    def __init__(self, cls_num=0, scale=1):
        super(SpatialGather_Module, self).__init__()
        self.cls_num = cls_num
        self.scale = scale

    def forward(self, pixel_rep, sft_obj_rgn):
        # sft_obj_rgn : torch.Size([1, 19, 128, 256])
        # pixel_rep   : torch.Size([1, 512, 128, 256])

        batch_size, c, h, w = sft_obj_rgn.size(0), sft_obj_rgn.size(1), sft_obj_rgn.size(2), sft_obj_rgn.size(3)
        sft_obj_rgn = sft_obj_rgn.view(batch_size, c, -1)
        pixel_rep = pixel_rep.view(batch_size, pixel_rep.size(1), -1)
        pixel_rep = pixel_rep.permute(0, 2, 1) # batch x hw x c

        sft_obj_rgn = F.softmax(self.scale * sft_obj_rgn, dim=2)# batch x k x hw

        # sft_obj_rgn: m_ki,  pixel_rep: x_i
        ocr_context = torch.matmul(sft_obj_rgn, pixel_rep).permute(0, 2, 1).unsqueeze(3) # batch x k x c
        return ocr_context
```

kth object region, forming the kth object region representation:

$$\mathbf{f}_k = \sum_{i \in \mathcal{I}} \tilde{m}_{ki} \mathbf{x}_i. \quad (4)$$

- $\mathbf{x}_i$ is the representation of pixel p_i.
- $\tilde{m}_{ki}$ is the normalized degree for pixel p_i belonging to the kth object region.
  - Soft object regions $(\mathbf{M}_1, \mathbf{M}_2, \cdots, \mathbf{M}_K)$ are spatially softmax-normalized as the weights $\tilde{m}$.

4. Augmented Representations $\mathbf{z}_i$

Augmented Representations $\mathbf{z}_i$

[Code]

▼ `augmented_rep`

```
# 4. Augmented Representations z_i : torch.Size([1, 512, 256, 512])
augmented_rep = self.ocr_distri_head(pixel_rep, obj_rgn_rep)
```

▼ `self.ocr_distri_head`

```
self.ocr_distri_head = SpatialOCR_Module(in_channels=ocr_mid_channels,
                                         key_channels=ocr_key_channels,
                                         out_channels=ocr_mid_channels,
                                         scale=1,
                                         dropout=0.05,
                                         )
```

▼ `SpatialOCR_Module`

```
class SpatialOCR_Module(nn.Module):
    """
```

[Concept]

- The final representation for pixel p_i is updated as the aggregation of two parts, (1) the original representation $\mathbf{x}_i$, and (2) the object contextual representation $\mathbf{y}_i$:

$$\mathbf{z}_i = g([\mathbf{x}_i^\top \ \mathbf{y}_i^\top]^\top). \quad (6)$$

  - $g(\cdot)$ is a transform function used to fuse the original representation and the object contextual representation, implemented by 1 × 1 conv → BN → ReLU.

```
    Implementation of the OCR module:
    We aggregate the global object representation to update the representation for each pixel.
    """
    def __init__(self,
                 in_channels,
                 key_channels,
                 out_channels,
                 scale=1,
                 dropout=0.1,
                 bn_type=None):
        super(SpatialOCR_Module, self).__init__()
        self.object_context_block = ObjectAttentionBlock2D(in_channels,
                                                           key_channels,
                                                           scale,
                                                           bn_type)
        _in_channels = 2 * in_channels

        self.conv_bn_dropout = nn.Sequential(
            nn.Conv2d(_in_channels, out_channels, kernel_size=1, padding=0, bias=False),
            ModuleHelper.BNReLU(out_channels, bn_type=bn_type),
            nn.Dropout2d(dropout)
        )

    def forward(self, pixel_rep, obj_rgn_rep):

        # Object Contextual Representations y_i : torch.Size([1, 512, 256, 512])
        obj_context_rep = self.object_context_block(pixel_rep, obj_rgn_rep)

        # Aggregation [x_i, y_i] : torch.Size([1, 1024, 256, 512])
        orig_rep_ocr_rep = torch.cat([obj_context_rep, pixel_rep], 1)

        # 4. Augmented Representations z_i : torch.Size([1, 512, 256, 512])
        output = self.conv_bn_dropout(orig_rep_ocr_rep)

        return output
```

Object Contextual Representations $\mathbf{y}_i$

[Code]

▼ `obj_context_rep`

```
# Object Contextual Representations y_i : torch.Size([1, 512, 256, 512])
obj_context_rep = self.object_context_block(pixel_rep, obj_rgn_rep)
```

▼ `ObjectAttentionBlock2D`

```
class ObjectAttentionBlock2D(_ObjectAttentionBlock):
    def __init__(self,
                 in_channels,
                 key_channels,
                 scale=1,
                 bn_type=None):
        super(ObjectAttentionBlock2D, self).__init__(in_channels,
                                                     key_channels,
                                                     scale,
                                                     bn_type=bn_type)
```

▼ `_ObjectAttentionBlock`

```
class _ObjectAttentionBlock(nn.Module):
    '''
    The basic implementation for object context block
    Input:
        N X C X H X W
    Parameters:
        in_channels       : the dimension of the input feature map
```

[Concept]

- The object contextual representation $\mathbf{y}_i$ for pixel p_i is computed according to Equation 3.

$$\mathbf{y}_i = \rho\left(\sum_{k=1}^{K} w_{ik}\delta(\mathbf{f}_k)\right), \quad (3)$$

  - $\delta(\cdot)$ and $\rho(\cdot)$ are both transformation functions implemented by 1 × 1 conv → BN → ReLU
  - w_{ik} is the relation between each pixel and each object region and computed as below:

$$w_{ik} = \frac{e^{\kappa(\mathbf{x}_i, \mathbf{f}_k)}}{\sum_{j=1}^{K} e^{\kappa(\mathbf{x}_i, \mathbf{f}_j)}}. \quad (5)$$

    - $\kappa(\mathbf{x}, \mathbf{f}) = \phi(\mathbf{x})^T\psi(\mathbf{f})$ is the unnormalized relation function
    - $\phi(\cdot)$ and $\psi(\cdot)$ are two transformation functions implemented by 1 × 1 conv → BN → ReLU.

```
        key_channels      : the dimension after the key/query transform
        scale             : choose the scale to downsample the input feature maps (save memory cost)
        bn_type           : specify the bn type
    Return:
        N X C X H X W
    '''
    def __init__(self,
                 in_channels,
                 key_channels,
                 scale=1,
                 bn_type=None):
        super(_ObjectAttentionBlock, self).__init__()
        self.scale = scale
        self.in_channels = in_channels
        self.key_channels = key_channels
        self.pool = nn.MaxPool2d(kernel_size=(scale, scale))
        self.f_pixel = nn.Sequential(
            nn.Conv2d(in_channels=self.in_channels, out_channels=self.key_channels,
                kernel_size=1, stride=1, padding=0, bias=False),
            ModuleHelper.BNReLU(self.key_channels, bn_type=bn_type),
            nn.Conv2d(in_channels=self.key_channels, out_channels=self.key_channels,
                kernel_size=1, stride=1, padding=0, bias=False),
            ModuleHelper.BNReLU(self.key_channels, bn_type=bn_type),
        )
        self.f_object = nn.Sequential(
            nn.Conv2d(in_channels=self.in_channels, out_channels=self.key_channels,
                kernel_size=1, stride=1, padding=0, bias=False),
            ModuleHelper.BNReLU(self.key_channels, bn_type=bn_type),
            nn.Conv2d(in_channels=self.key_channels, out_channels=self.key_channels,
                kernel_size=1, stride=1, padding=0, bias=False),
            ModuleHelper.BNReLU(self.key_channels, bn_type=bn_type),
        )
        self.f_down = nn.Sequential(
            nn.Conv2d(in_channels=self.in_channels, out_channels=self.key_channels,
                kernel_size=1, stride=1, padding=0, bias=False),
            ModuleHelper.BNReLU(self.key_channels, bn_type=bn_type),
        )
        self.f_up = nn.Sequential(
            nn.Conv2d(in_channels=self.key_channels, out_channels=self.in_channels,
                kernel_size=1, stride=1, padding=0, bias=False),
            ModuleHelper.BNReLU(self.in_channels, bn_type=bn_type),
        )

    def forward(self, pixel_rep, obj_rgn_rep):
        batch_size, h, w = pixel_rep.size(0), pixel_rep.size(2), pixel_rep.size(3)
        if self.scale > 1:
            pixel_rep = self.pool(pixel_rep)

        # phi()
        query = self.f_pixel(pixel_rep).view(batch_size, self.key_channels, -1)
        query = query.permute(0, 2, 1)

        # psi()
        key = self.f_object(obj_rgn_rep).view(batch_size, self.key_channels, -1)

        # Pixel-Region Relation delta()
        value = self.f_down(obj_rgn_rep).view(batch_size, self.key_channels, -1)
        value = value.permute(0, 2, 1)

        # kappa() = phi()^T psi()
        sim_map = torch.matmul(query, key)
        sim_map = (self.key_channels**-.5) * sim_map

        # w_ik
        sim_map = F.softmax(sim_map, dim=-1)
        print(f"[w_ik] relation between pixel and object region : {sim_map.shape}")

        # w_ik * delta()
        context = torch.matmul(sim_map, value)
        context = context.permute(0, 2, 1).contiguous()
        context = context.view(batch_size, self.key_channels, *x.size()[2:])

        # rho()
        context = self.f_up(context)
        if self.scale > 1:
```

```
            context = F.interpolate(input=context, size=(h, w), mode='bilinear', align_corners=ALIGN_CORNERS)

        return context
```

5. Final Segmentation Output

[Code]

▼ `out`

```
# 5. Final Segmentation Output : torch.Size([1, 19, 256, 512])
out = self.cls_head(augmented_rep)
```

▼ `self.cls_head`

```
self.cls_head = nn.Conv2d(
            ocr_mid_channels,
            config.DATASET.NUM_CLASSES,
            kernel_size=1, stride=1, padding=0,
 bias=True)
```

[Concept]

- We predict the final segmentation from the final representation using a linear function and we also apply a pixel-wise cross-entropy loss on the final segmentation prediction.