DeCoupledDeepNeuralNetworkForSemiSupervise

Decoupled Deep Neural Network for Semi-supervised Semantic Segmentation

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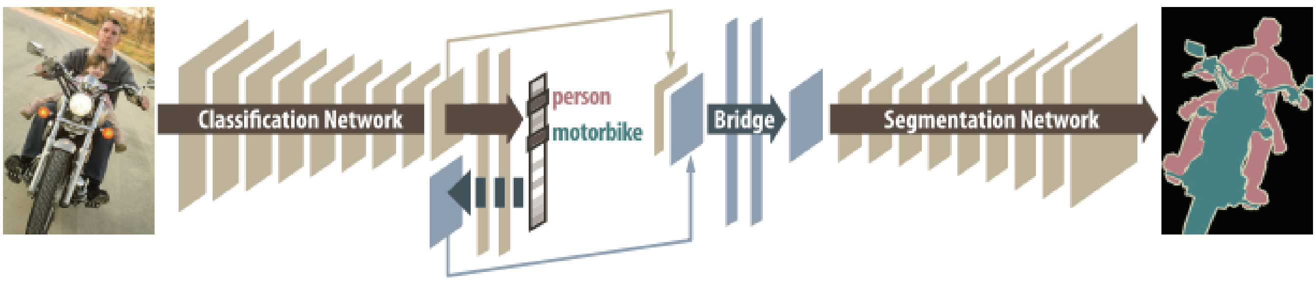
- Decouples classification and Segmentation
- First labels are identified by classification network and then binary segmentation is performed for each of the identified labels.
- Use of Heterogeneous annotations (strong annotations: segmentation masks and weak annotations: object class labels per image)
- Advantages:
    - Reduction in search space for segmentation by exploiting class-speicific activation maps.
- Common challenges in Semantic Segmentation:
    - Pose Variations.
    - Scale changes.
    - Occlusion
    - Background clutter
- **Semi and weakly-supervised approaches update the model of a supervised DNN by iteratively inferring and refining hypothetical segmentation labels.**
- These methods rely on ad-hoc procedures and there is no guarantee convergence; implementation may be tricky and results may be difficult to reproduce.
- **BRIDGING-LAYERS:**Deliver class-specific information; enable segmentation network to focus on the single label for segmentation (causing a reduction in search space.)
- **Note:**
    - Training is performed on each network separately. Classification is trained on image-level annotations and Segmentation is trained on pixel-wise annotations.
- Semi-Supervised learning bridges the gap between fully- and weakly-supervised learning approaches.
- Architecture:



    - **Classification Network:**

- Takes an image x as its input, and outputs a normalized score vector $S\left(\mathbf{x};\theta_c\right) \in \mathbf{R}^L$ representing scores of the input x based on trained classification model θ_c for predefined L categories.
- The objective of the Classification Network is:

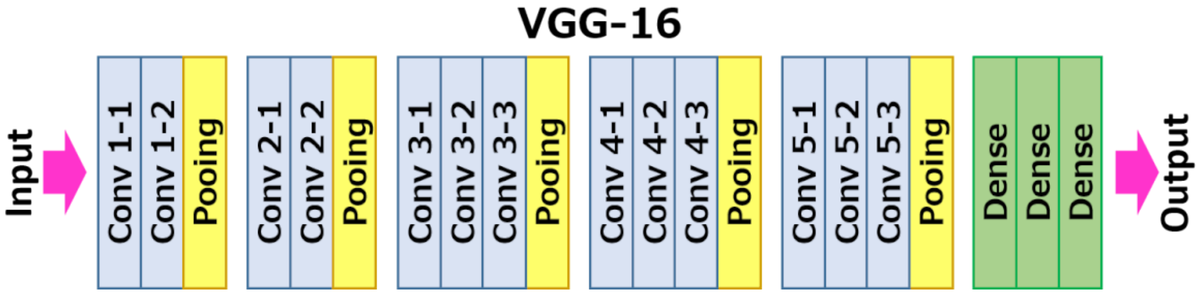
$$\min_{\theta_e} \sum_i e_c\left(\mathbf{y}_i, S\left(\mathbf{x}_i;\theta_c\right)\right)$$

- here $\mathbf{y}_i \in \{0,1\}^L$ denotes the ground-truth label vector of the i-th example; e_c represents the error/loss.
- VGG-16 is used for classifcation
- The region in x_i corresponding to each label $l \in \mathcal{L}_i$ is predicted by the Segmentation Network.

- **Segmentation Network:**
  - Input: class-specific activation map g_i^l of input image x_i, obtained from ***bridging layers***
  - Output: 2 channel class-specific segmentation map $M\left(\mathbf{g}_i^l;\theta_s\right)$, θ_s is the model parameter for segmentation network. It has foreground channel and background channel represented as: $M_f\left(\mathbf{g}_i^l;\theta_s\right)$ and $M_b\left(\mathbf{g}_i^l;\theta_s\right)$ respectively.
  - Objective function:

$$\min_{\theta_s} \sum_i e_s\left(\mathbf{z}_i^l, M\left(\mathbf{g}_i^l;\theta_s\right)\right)$$

  - It is formulated as per-pixel regression to ground-truth segmentation and minimized the above objective.
  - here z_i^l represents the binary ground-truth segmentation mask for category l of the i-th image x_i.
  - **Deconvolution network is used for segmentation, which uses a sequence of unpooling, deconvolution and rectification**.
  - Unpooling is implemented by importing the switch variable from every pooling layer in the classification network.
  - **SWITCH VARIABLE is nothing but the pooling indices of the pooling layer.**
  - The objective is to minimize the pixel-wise *binary* classification; it infers whether each pixel belongs to the given class l or not.
  - Normally we try to classify each pixel to one of the L predefined classes.
  - By decoupling classification and segmentation we have reduced the number of parameters to be optimized since it is a binary classification for segmenting each class label.
  - This decoupling is helpful since we have only 5-10 fully annotated images per class.
- **Bridging Layers:**
  - To construct the class specific activation map g_i^l for each identified label $l \in \mathcal{L}_i$.

- To encode spatial configuration of objects presented in image, we exploit outputs from and intermediate layer in the classification network.
- Outputs from the last pooling layer $pool5$ since the activation patterns of convolution and pooling layers often preserve spatial information effectively.
- Here we will represent the $pool5$ layer as f_{spat}.
- 

- Let $f^{(i)}$ be the output of the i-th layer (i=1,2,3..M) in the classification network. The relevance of activations in $f^{(i)}$ with respect to a specific class l is computed by chain rule of partial derivative, which is similar to error back-propagation in optimization, as

$$\mathbf{f}^l_{\mathrm{cls}} = \frac{\partial S_l}{\partial \mathbf{f}^{(k)}} = \frac{\partial \mathbf{f}^{(M)}}{\partial \mathbf{f}^{(M-1)}} \frac{\partial \mathbf{f}^{(M-1)}}{\partial \mathbf{f}^{(M-2)}} \cdots \frac{\partial \mathbf{f}^{(k+1)}}{\partial \mathbf{f}^{(k)}}$$

- where f^l_{cls} denotes class-specific saliency map and S_l is the classification score of class l.
- where $\mathbf{f}^l_{\mathrm{cls}}$ denotes class-specific saliency map and S_l is the classification score of class l.
- Intuitively, the above equation means that the values in $\mathbf{f}^l_{\mathrm{cls}}$ depend on how much the activation in $f^{(k)}$ are relevant to class l; this is measured by computing the partial-derivative of class score S_l with respect to the activations in $f^{(k)}$. We back-propagate the class-specific information until $pool5$ layer.
- **The class-specific activation map g^l_i is obtained by combining both f_{spat} and f^l_{cls}.**
- We first concatenate $\mathbf{f}_{\mathrm{spat}}$ and $\mathbf{f}^l_{\mathrm{cls}}$ in their channel direction, and forward-propagate it through the fully-connected bridging layers, which discover the optimal combination of $\mathbf{f}_{\mathrm{spat}}$ and $\mathbf{f}^l_{\mathrm{cls}}$ using the trained weights.
- The resultant class-specific activation map g^l_i that contains both spatial and class-specific information is given to segmentation network to produce a class-specific segmentation map.
- **The changes in g^l_i depend only on f^l_{cls} since f_{spat} is fixed for all classes in an input image.**

Figure 2: Examples of class-specific activation maps (output of bridging layers). We show the most representative channel for visualization. Despite significant variations in input images, the class-specific activation maps share similar properties.

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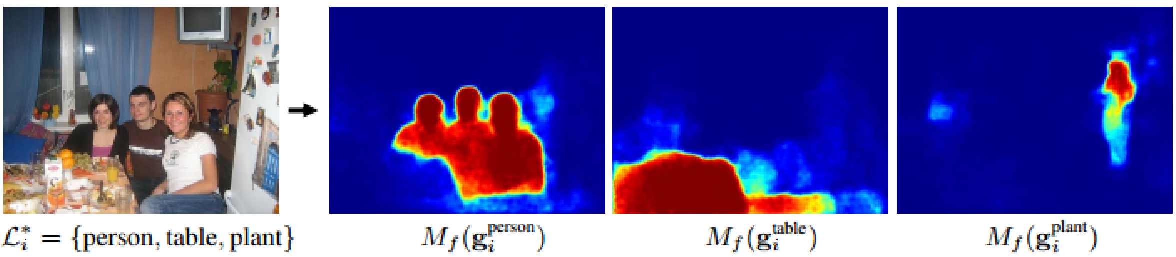
    - The activations from the images in the same class share similar patterns despite substantial appearance variations, which shows that the output of bridging layers capture **class-specific informations** effectively.
    - It also reduces the variations of input distributions for segmentation network, which allows to achieve good generaliation performance in segmentation even with a small number of training examples.
- **Inference:**
    - We compute a class-specific activation map g_i^l for each identified label $l \in L_i$ and obtaion class-specific segmenation maps $\left\{M\left(\mathbf{g}_i^l;\theta_s\right)\right\}_{\forall l \in \mathcal{L}_i}$.
    - We also obtain $M\left(\mathbf{g}_i^*;\theta_s\right)$, where g_i^* is the activation map from the bridging layers for all identified labels.
    - The final label estimation is given by identifying the label with the maximum score in each pixel out of $\left\{M_f\left(\mathbf{g}_i^l;\theta_s\right)\right\}_{\forall l \in \mathcal{L}_l}$ and $M_b\left(\mathbf{g}_i^*;\theta_s\right)$.
    - 

    Figure 3: Input image (left) and its segmentation maps (right) of individual classes.
    - The above image illustrates the output segmentation map of each g_i^l for x_i, where each map identifies high response area given g_i^l successfully.