Semantic Segmentation

CS 4391 Introduction Computer Vision
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Conditional Random Fields Meet Deep Neural Networks for Semantic Segmentation. Arnab et al., IEEE SIGNAL PROCESSING MAGAZINE, 2018
Semantic Segmentation

- Label pixels into semantic classes

- Naïve method
  - Classify each pixel independently

- Better idea
  - Using context of pixels
Conditional Random Fields (CRFs)

• Pixel labeling problem

\[ \text{graph } \mathcal{G} = (\mathcal{V}, \mathcal{E}) \]

2D grid for images

\[ X_1 \in \{\text{bg, cat, dog, person}\} \]
Conditional Random Fields (CRFs)

• Model the conditional probability distribution

\[ P(\mathbf{X} | \mathbf{I}) = \frac{1}{Z(I)} \exp\left( - \sum_{c \in C_G} \phi_c(\mathbf{X}_c | \mathbf{I}) \right) \]

**Diagram:**
- **Label** and **image**
- **Partition function** (normalization factor)
- **clique** and **Potential function**

**Graph:**
\[ \mathcal{G} = (\mathcal{V}, \mathcal{E}) \]

2D grid for images

\[ x_i \in \{bg, cat, dog, person\} \]
Conditional Random Fields (CRFs)

\[ P(X|I) = \frac{1}{Z(I)} \exp\left(-\sum_{c \in C_G} \phi_c(X_c|I)\right) \]

- Energy function

\[ E(x|I) = \sum_{c \in C_G} \phi_c(x_c|I) \quad x \in \mathcal{L}^N \]

\[ P(x|I) = \frac{1}{Z(I)} \exp(-E(x|I)) \quad Z(I) = \sum_x \exp(-E(x|I)) \]

- Maximum a posteriori (MAP) labeling

\[ x^* = \arg \max_{x \in \mathcal{L}^N} P(x|I) \]
Conditional Random Fields (CRFs)

• Unary potential and pairwise potential

\[ E(x, I) := \sum_{u \in V} \psi_u(X_u = x_u | I) + \sum_{\{u,v\} \in E} \psi_{u,v}(X_u = x_u, X_v = x_v | I) \]

  E.g., classifier output  \hspace{1cm}  E.g., smoothing pairwise potential \[ x_u \neq x_v \]

• Energy minimization problem
  • NP-hard
  • Exact and approximate algorithms exist to obtain acceptable solutions

Conditional Random Fields (CRFs)

Efficient Inference in Fully Connected CRFs with Gaussian Edge Potentials. Krähenbühl & Koltun, NeurIPS, 2011

Conditional Random Fields Meet Deep Neural Networks for Semantic Segmentation. Arnab et al., IEEE SIGNAL PROCESSING MAGAZINE, 2018
Combining Neural Networks with CRFs

- Utilize neural networks to compute unary potentials

Better classifier

Semantic image segmentation with deep convolutional nets and fully connected CRFs. Chen et al., ICLR, 2015.

Conditional Random Fields Meet Deep Neural Networks for Semantic Segmentation. Arnab et al., IEEE SIGNAL PROCESSING MAGAZINE, 2018
Atrous convolution

\[
y[i] = \sum_{k=1}^{K} x[i + r \cdot k] w[k]
\]

Fully Convolutional Networks

• Adapt classification networks for dense prediction

Treat FC layers as convolutions with kernels that cover the entire input regions
Fully Convolutional Networks

• Convert AlexNet

[224x224x3] INPUT
[55x55x96] CONV1: 96 11x11 filters at stride 4, pad 0
[27x27x96] MAX POOL1: 3x3 filters at stride 2
[27x27x96] NORM1: Normalization layer
[27x27x256] CONV2: 256 5x5 filters at stride 1, pad 2
[13x13x256] MAX POOL2: 3x3 filters at stride 2
[13x13x256] NORM2: Normalization layer
[13x13x384] CONV3: 384 3x3 filters at stride 1, pad 1
[13x13x384] CONV4: 384 3x3 filters at stride 1, pad 1
[13x13x256] CONV5: 256 3x3 filters at stride 1, pad 1
[6x6x256] MAX POOL3: 3x3 filters at stride 2
[4096] FC6: 4096 neurons
[4096] FC7: 4096 neurons
[1000] FC8: 1000 neurons (class scores)

Fully Convolutional Networks for Semantic Segmentation. Long et al., CVPR, 2015
Fully Convolutional Networks

• Deconvolution for up-sampling

Input: 2 x 2

3 x 3 “deconvolution”, stride 2, pad 1

Output: 4 x 4

Sum where output overlaps

Input gives weight for filter

Fully Convolutional Networks for Semantic Segmentation. Long et al., CVPR, 2015
Fully Convolutional Networks

• Combine predictions with different resolutions
U-Net

Convolutional Networks for Biomedical Image Segmentation, Ronneberger et al., MICCAI 2015
Instance Segmentation

• Separate object instances in the same class
• Detection + segmentation

https://ai-pool.com/d/could-you-explain-me-how-instance-segmentation-works
Mask R-CNN

‘res5’ denotes ResNet’s fifth stage

Mask R-CNN. He et al., ICCV, 2017
RoI Pooling vs. RoI Align

RoI \((x, y, h, w)\)

RoI mapping to feature map

\[ s \times (x, y, h, w) \]

\[ s = \frac{1}{16} \]

RoI Pooling

RoI Align
## Mask R-CNN

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<th>align?</th>
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Mask R-CNN. He et al., ICCV, 2017
Summary

• Semantic segmentation
  • Label pixels into object classes
  • Traditional methods: conditional random fields
  • Deep learning methods: deconvolution, atrous convolution

• Instance segmentation
  • Separate object instances in the same class
  • Detection + segmentation inside each box
Further Reading

• Fully-connect CRFs, 2011 https://arxiv.org/abs/1210.5644
• FCN, 2015 https://arxiv.org/abs/1411.4038
• Unet, 2015 https://arxiv.org/abs/1505.04597