

Statistical Methods in AI (CSE/ECE 471)

Transfer Learning, Landscape of CNNs



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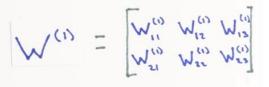




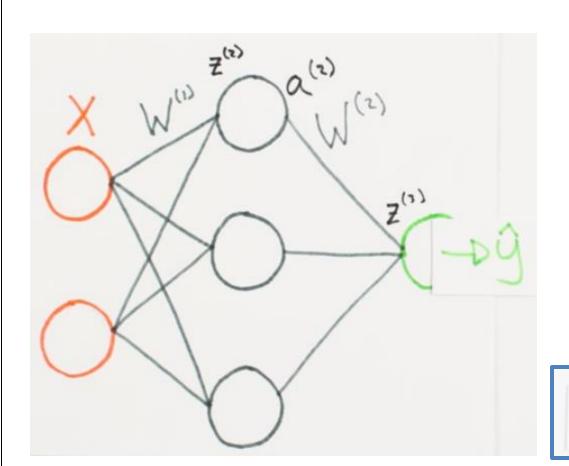
Center for Visual Information Technology (CVIT)
IIIT Hyderabad



Multi-Neuron Networks



$$\bigwedge_{(S)} = \begin{bmatrix} M_{ij}^{(s)} \\ M_{ij}^{(s)} \end{bmatrix}$$



$$z^{(2)} = XW^{(1)}$$

$$a^{(2)} = f(z^{(2)})$$

$$z^{(3)} = a^{(2)}W^{(2)}$$

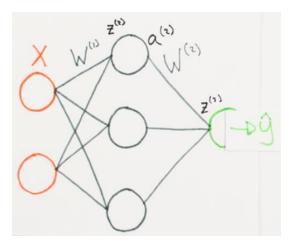
$$\hat{y} = f(z^{(3)})$$

$$J = \sum \frac{1}{2} (y - \hat{y})^2$$
(5)

$$J = \sum_{i=1}^{n} \frac{1}{2} (y - f(f(XW^{(1)})) W^{(2)})^{2}$$



Multi-Neuron Networks :: Backpropagation



$$J = \sum \frac{1}{2} (y - f(f(XW^{(1)})) W^{(2)}))^2$$

$$+ \text{How poss this change}$$

$$\text{The tense there?}$$

$$\frac{\partial J}{\partial W}$$

$$\bigwedge_{(s)} = \begin{bmatrix} M_{(s)}^{12} \\ M_{(s)}^{21} \\ M_{(s)}^{21} \end{bmatrix}$$

$$= \begin{bmatrix} M_{(s)}^{11} \\ M_{(s)}^{21} \\ M_{(s)}^{21} \end{bmatrix}$$

$$= \begin{bmatrix} M_{(s)}^{11} \\ M_{(s)}^{12} \\ M_{(s)}^{21} \end{bmatrix}$$

$$= \begin{bmatrix} M_{(s)}^{11} \\ M_{(s)}^{21} \\ M_{(s)}^{21} \\ M_{(s)}^{21} \end{bmatrix}$$

$$= \begin{bmatrix} M_{(s)}^{11} \\ M_{(s)}^{21} \\ M_{(s)}^{21} \\ M_{(s)}^{21} \end{bmatrix}$$

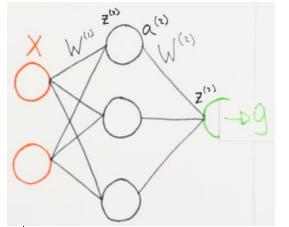
$$= \begin{bmatrix} M_{(s)}^{11} \\ M_{(s)}^{21} \\ M_{(s)}^{21} \\ M_{(s)}^{21} \\ M_{(s)}^{21} \end{bmatrix}$$

$$= \begin{bmatrix} M_{(s)}^{11} \\ M_{(s)}^{21} \\ M_{(s)}^{21} \\ M_{(s)}^{21} \\ M_{(s)}^{21} \\ M_{(s)}^{21} \end{bmatrix}$$

$$= \begin{bmatrix} M_{(s)}^{11} \\ M_{(s)}^{21} \\ M$$



Multi-Neuron Networks :: Backpropagation



$$z^{(2)} = XW^{(1)} \tag{1}$$

$$a^{(2)} = f(z^{(2)})$$
 (2)

$$z^{(3)} = a^{(2)} W^{(2)} \tag{3}$$

$$\hat{y} = f(z^{(3)})$$
 (4)

$$\mathcal{N}_{(5)} = \begin{bmatrix} \mathcal{N}_{(0)}^{12} \\ \mathcal{N}_{(0)}^{12} \end{bmatrix} = \begin{bmatrix} \frac{\partial \mathcal{N}_{(1)}}{\partial \mathbf{I}} \\ \frac{\partial \mathcal{N}_{(1)}}{\partial \mathbf{I}} \end{bmatrix} = \begin{bmatrix} \frac{\partial \mathcal{N}_{(1)}}{\partial \mathbf{I}} \\ \frac{\partial \mathcal{N}_{(1)}}{\partial \mathbf{I}} \end{bmatrix}$$

$$\mathcal{N}_{(1)} = \begin{bmatrix} \mathcal{N}_{(0)}^{11} & \mathcal{N}_{(0)}^{12} & \mathcal{N}_{(0)}^{12} \\ \mathcal{N}_{(0)}^{11} & \mathcal{N}_{(0)}^{12} & \mathcal{N}_{(0)}^{12} \end{bmatrix} = \begin{bmatrix} \frac{\partial \mathcal{N}_{(1)}}{\partial \mathbf{I}} & \frac{\partial \mathcal{N}_{(1)}}{\partial \mathbf{I}} & \frac{\partial \mathcal{N}_{(2)}}{\partial \mathbf{I}} \\ \frac{\partial \mathcal{N}_{(1)}}{\partial \mathbf{I}} & \frac{\partial \mathcal{N}_{(2)}}{\partial \mathbf{I}} & \frac{\partial \mathcal{N}_{(2)}}{\partial \mathbf{I}} \end{bmatrix}$$

$$|J = \left| \sum_{i=1}^{n} \frac{1}{2} \left| (y - \hat{y})^{2} \right| \right|$$

$$J = \sum \frac{1}{2} (y - f(f(XW^{(1)})) W^{(2)}))^{2}$$

$$\uparrow_{\text{HOW POES THIS CHANGE THESE?}}$$

$$\frac{\partial J}{\partial W}$$

$$\frac{\partial J}{\partial W^{(2)}} = (a^{(2)})^T \delta^{(3)}$$

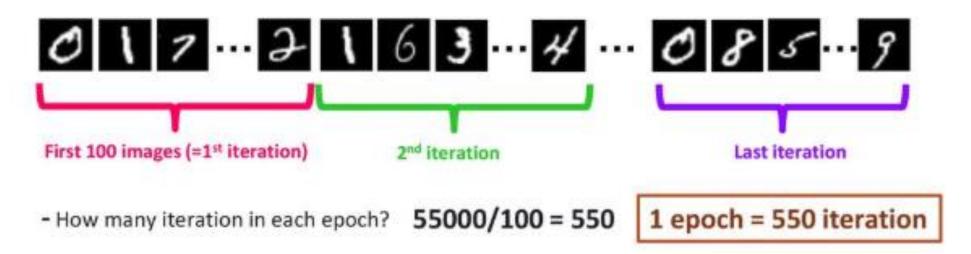
$$\delta^{(3)} = -(y - \hat{y})f'(z^{(3)})$$

$$\frac{\partial J}{\partial W^{(1)}} = X^T \delta^{(2)}$$

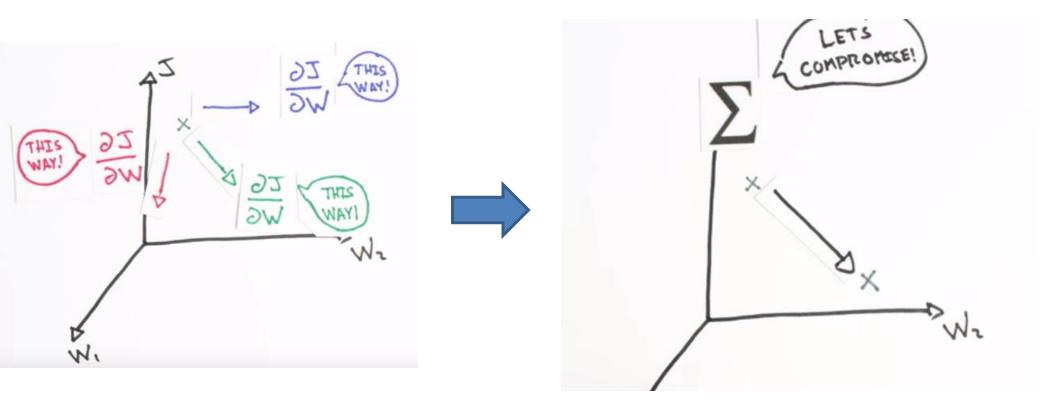
$$\delta^{(2)} = \delta^{(3)} (W^{(2)})^T f'(z^{(2)})$$

Epoch, Mini-batch, Iteration

- Mini-batch: Size of sample group being used to update weights
- Epoch = One full forward & backward pass over entire training data
- Iteration = # of forward and backward passes at mini-batch level
 - number of training data: N=55,000
 - Let's take batch size of B=100

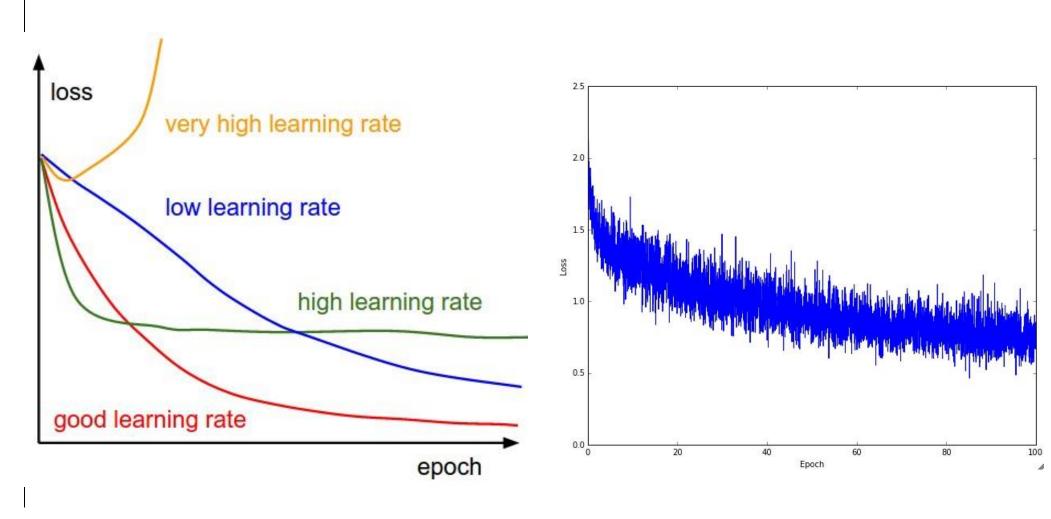


Mini-batch gradient descent



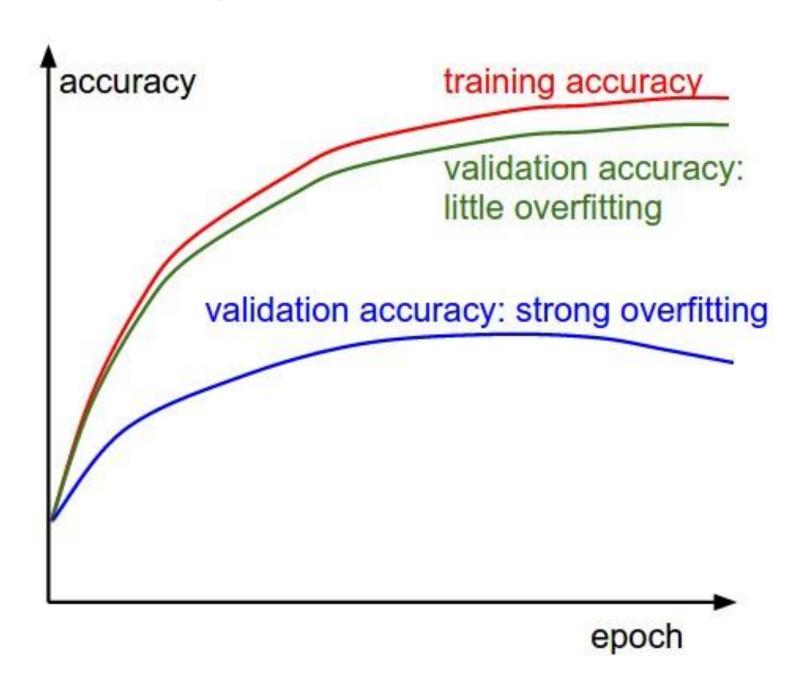


Training – setting learning rate





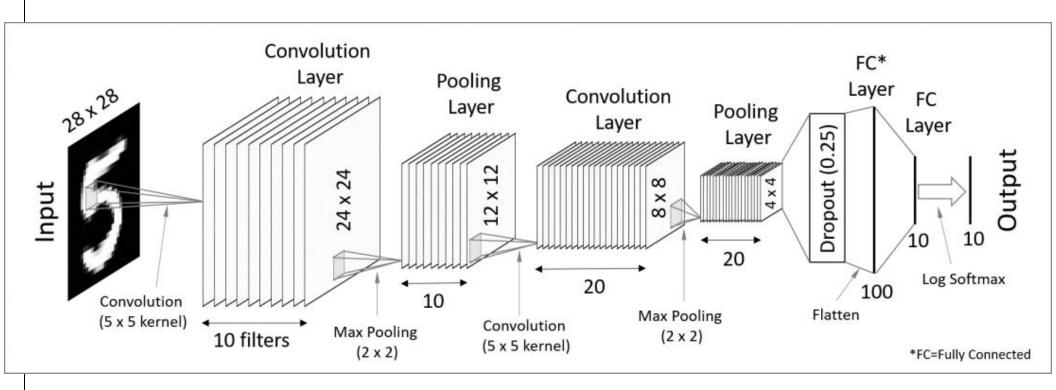
Monitoring





Recall: CNN

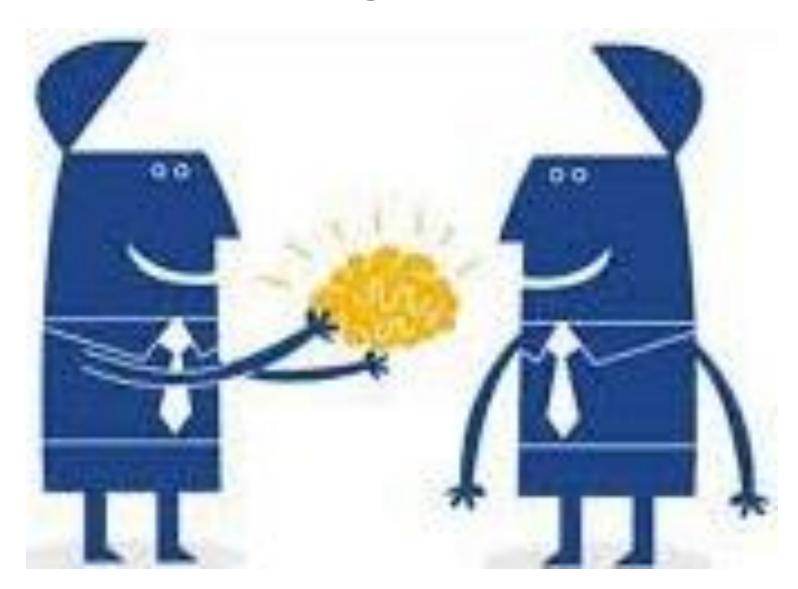








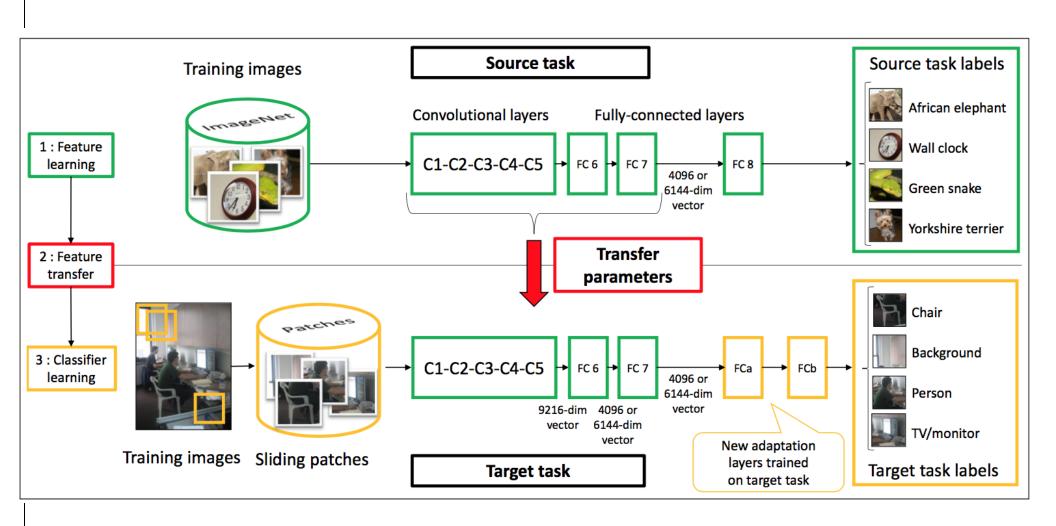
Transfer Learning





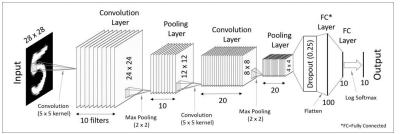


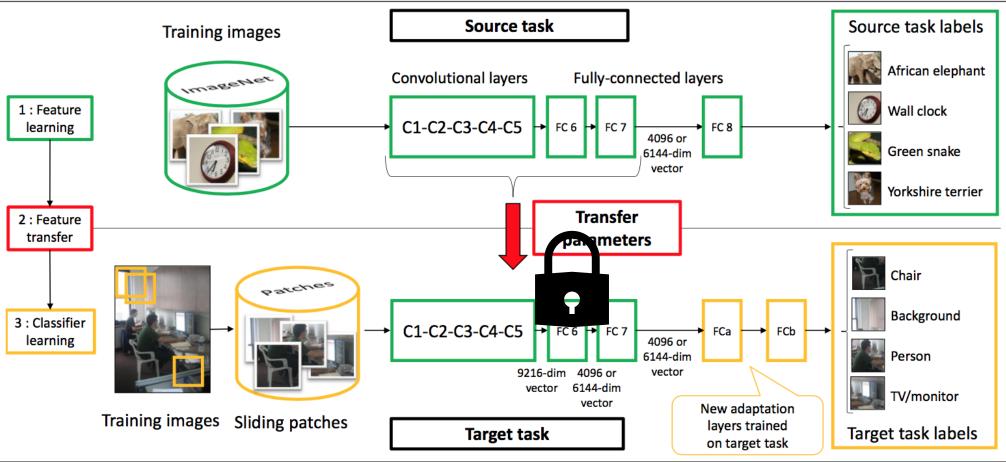






Transfer Learning: Approach-1

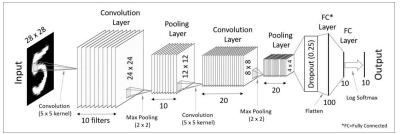


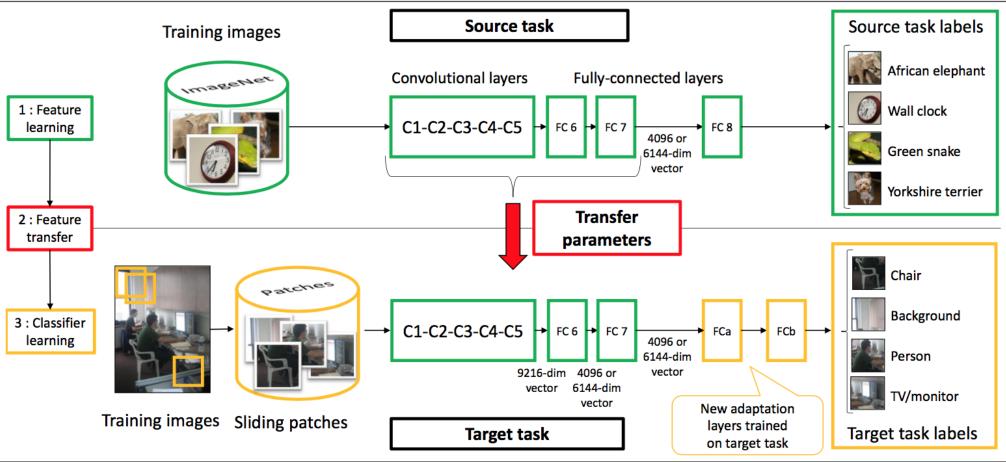


- Learn only weights for newly added layers.
- Ideal when 'new domain' data is small in quantity



Transfer Learning: Approach-2





- LR for new layer weights = 10 * source_Ir (for bias, 20 * source_Ir)
- Ideal when 'new domain' data is reasonably large or domain shift is significant





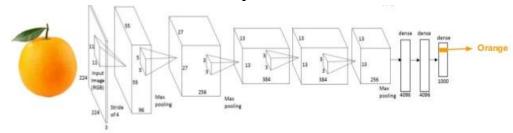
Landscape of CNNs: Applications and Architectures

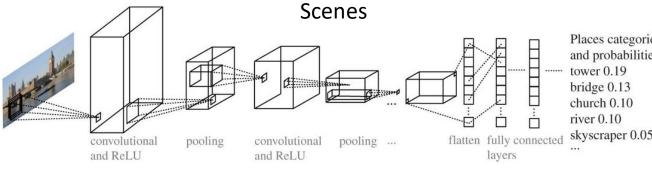


Image -> Label



Objects





Places categories and probabilities skyscraper 0.05

DeepFace Architecture

Faces

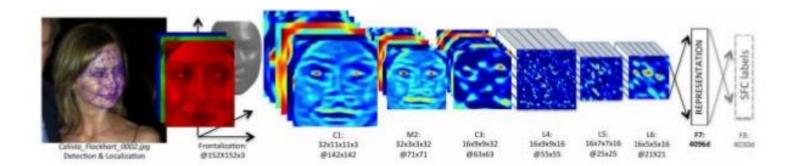
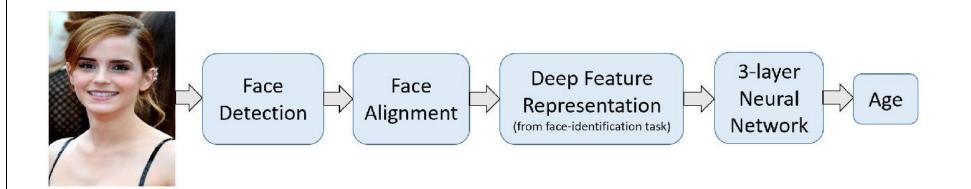


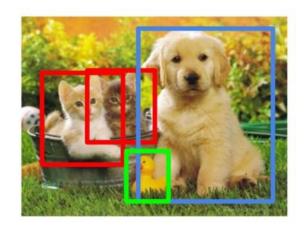


Image > Number





Object Detection



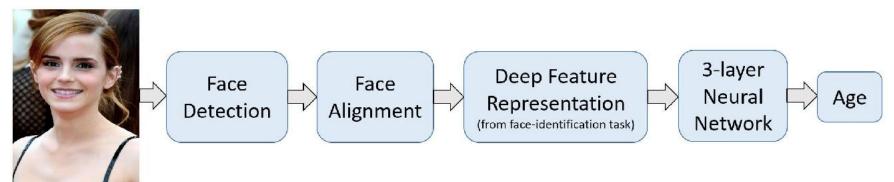
CAT, DOG, DUCK



Image > Number



Age Estimation



Object detection

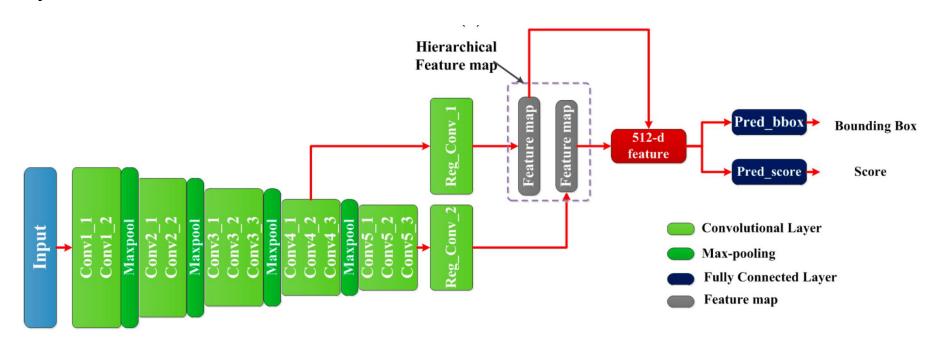
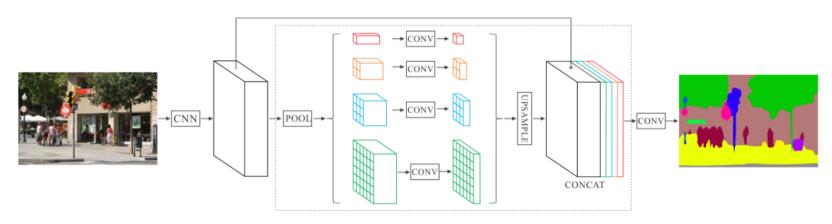




Image -> Label Image

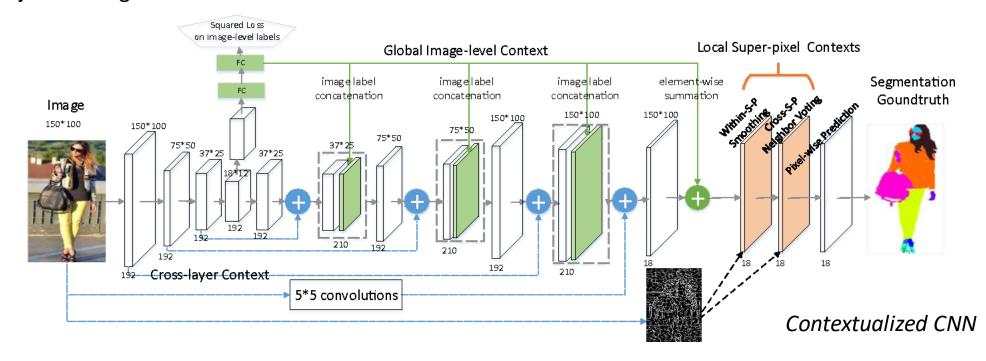


Scene Parsing



PSPNet

Object Parsing







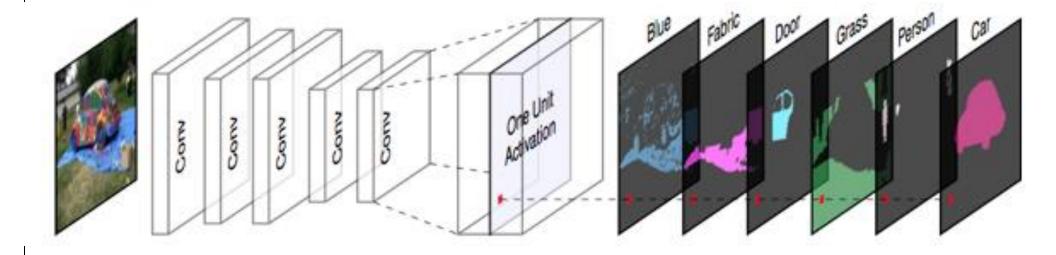
Semantic segmentation







Semantic segmentation



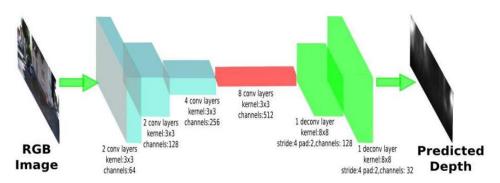
http://netdissect.csail.mit.edu/thumb/slides-thumbnail.png



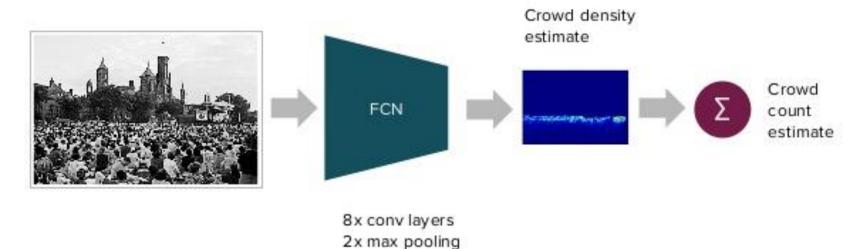
Image → Image



Depth Estimation



Crowd Counting



Marsden et al. Fully convolutional crowd counting on highly congested scenes. VISAPP 2017 https://arxiv.org/abs/1612.00220

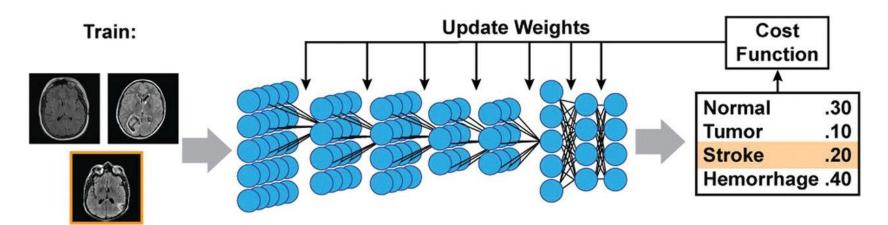


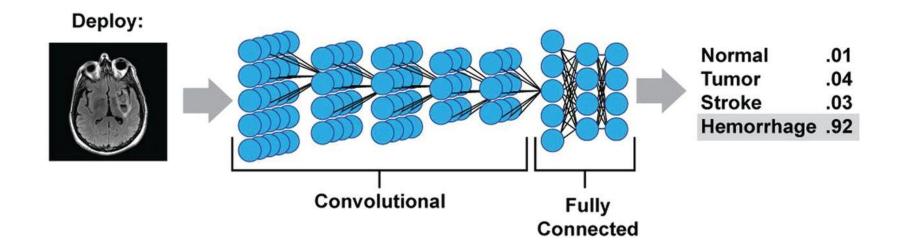
Multi-channel input



NeuroRadiology (fMRI)

Convolutional Neural Networks



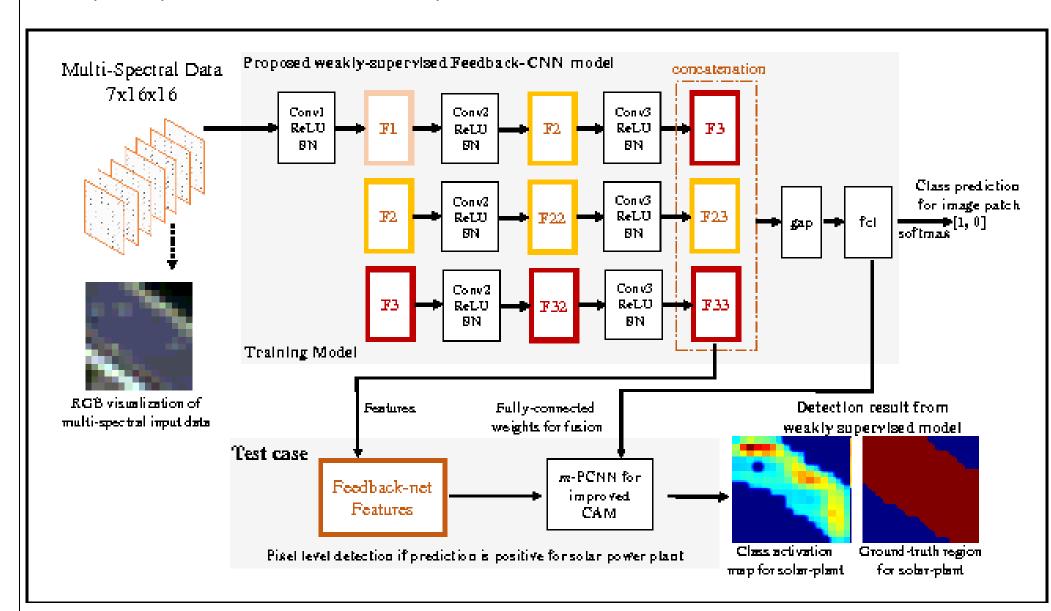






Multi-channel input

Solar-power plant detection from multi-spectral data



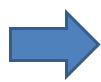


Multi-branch input



Image Colorization









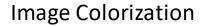


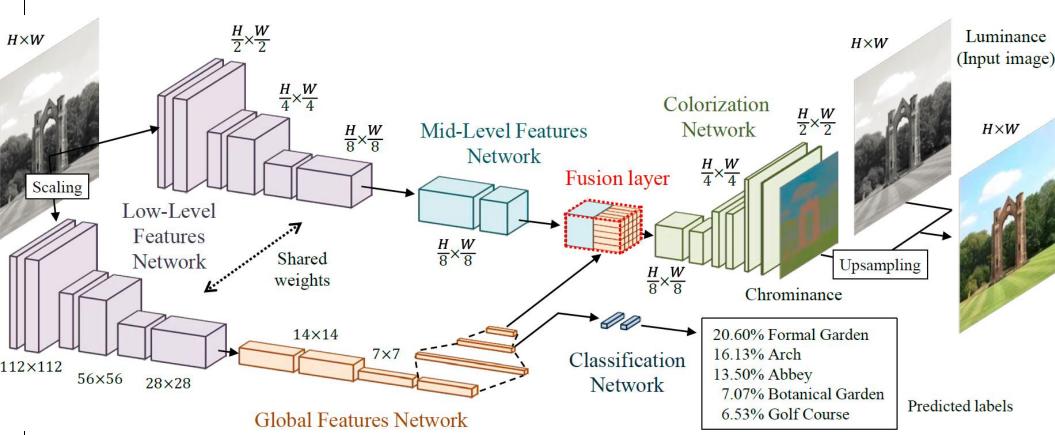












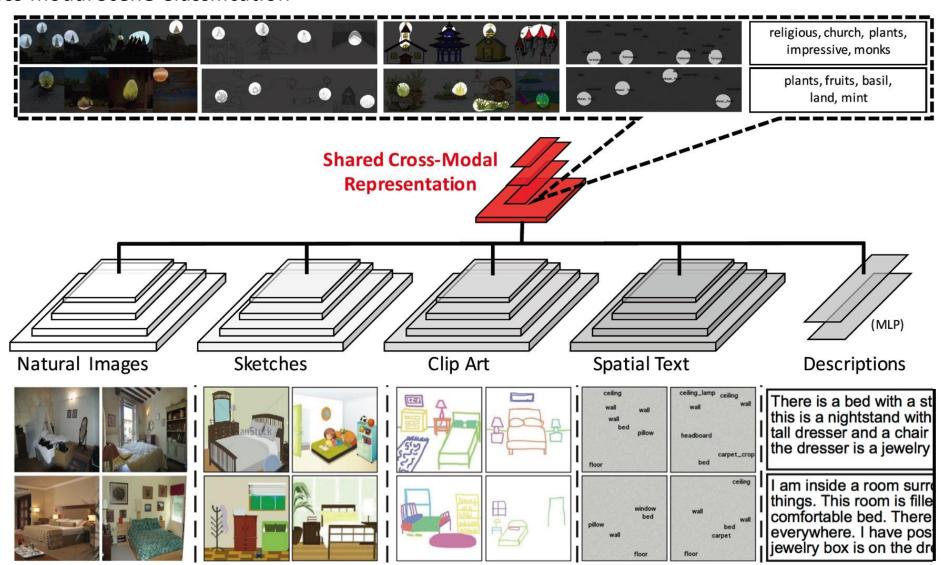
http://hi.cs.waseda.ac.jp/~iizuka/projects/colorization/en/



Multi-branch input



Cross-modal Scene Classification



http://projects.csail.mit.edu/cmplaces/



Multi-branch input



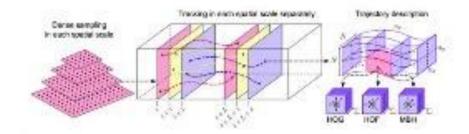
Activity Recognition

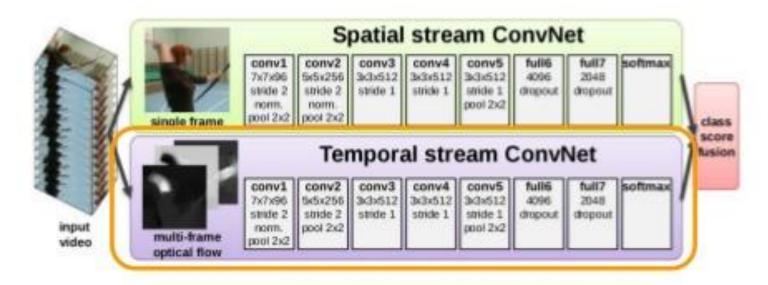
Recognition: Two stream

Two CNNs in paralel:

- One for RGB images
- One for Optical flow (hand-crafted features)

Fusion after the softmax layer





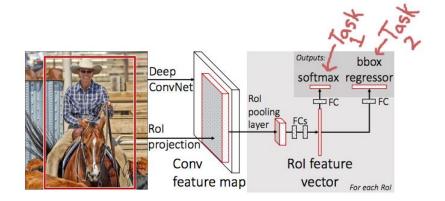
Simonyan, Karen, and Andrew Zisserman. "Two-stream convolutional networks for action recognition in videos." NIPS 2014.



Multi-branch output



Object Detection, Classification



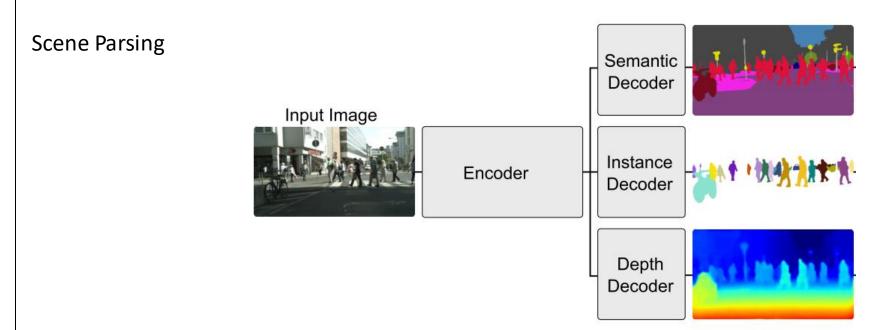




Image CNNs for non-image data



Audio Beat Detection

