Deep Learning for Computer Vision

CNNs for Other Image Tasks

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भारतीय प्रौद्योगिकी संस्थान हैदराबाद
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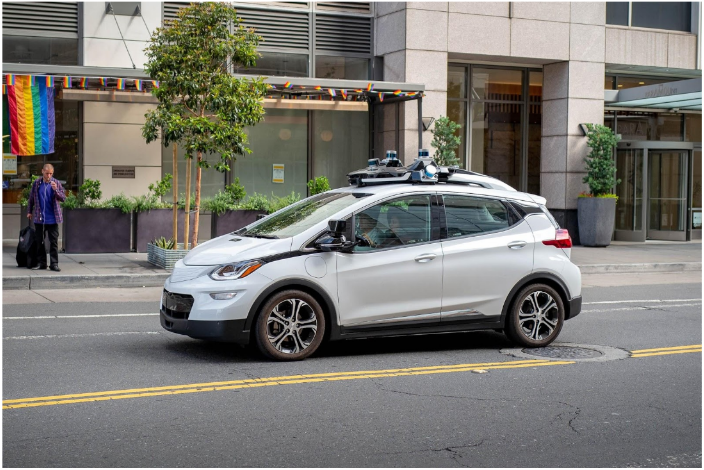
Depth Estimation



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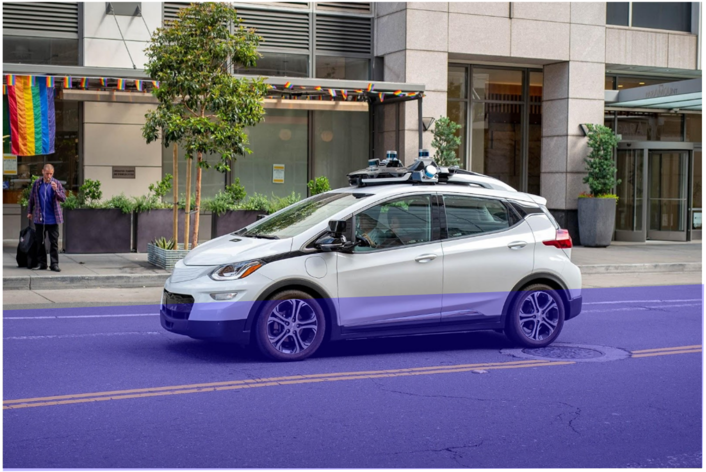

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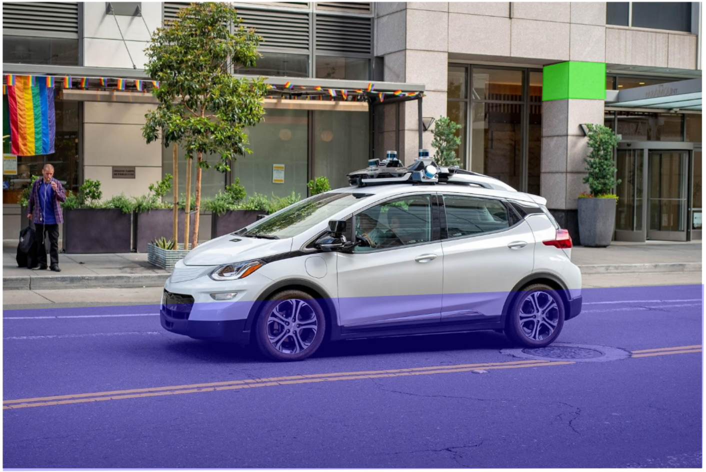

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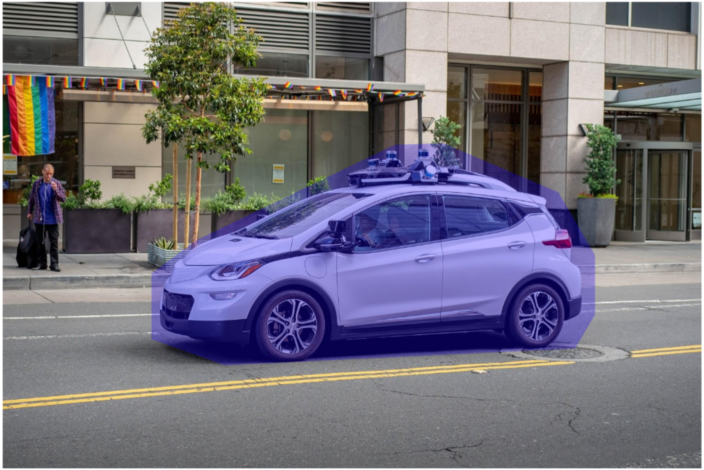

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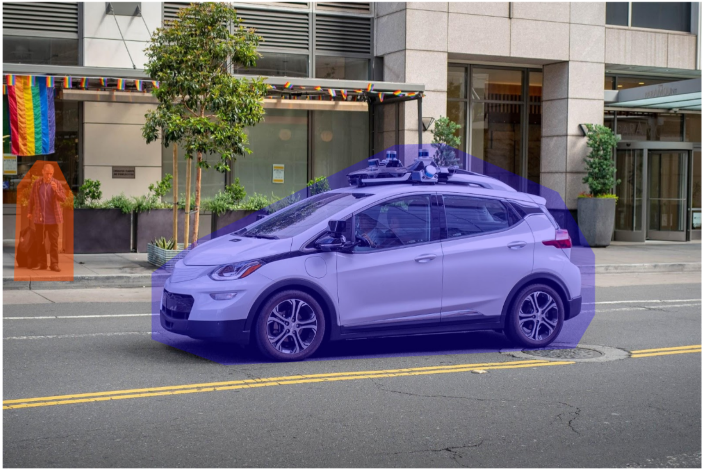

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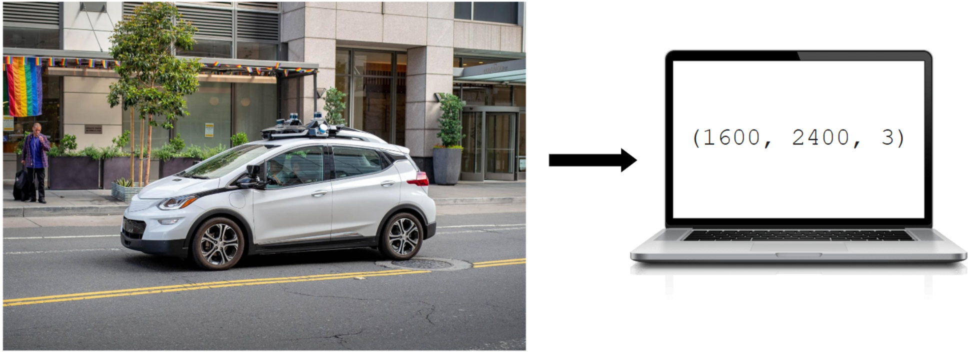

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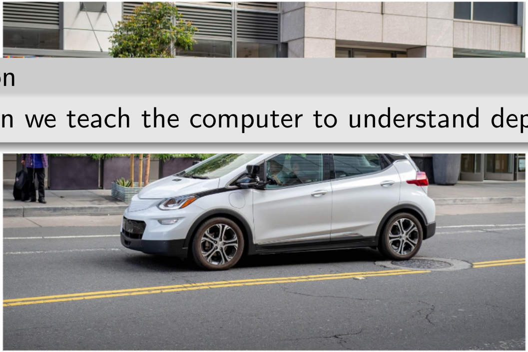
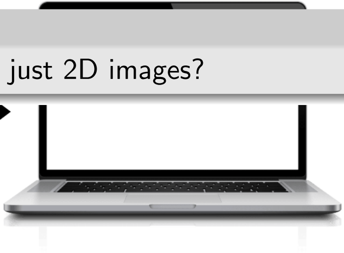
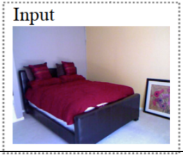




Question

How can we teach the computer to understand depth from just 2D images?

Depth Estimation from Single Image[1]



[1] Eigen et al, Depth map prediction from a single image using a multi-scale deep network, NeurIPS 2014

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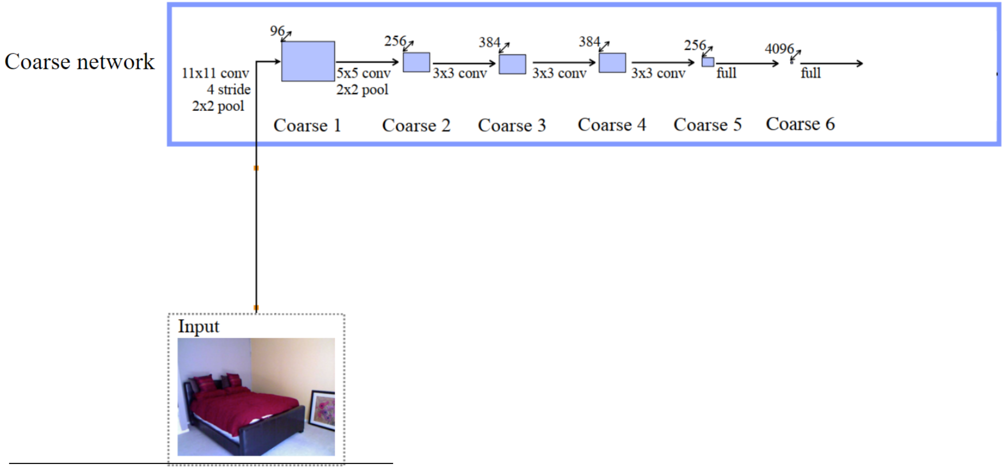

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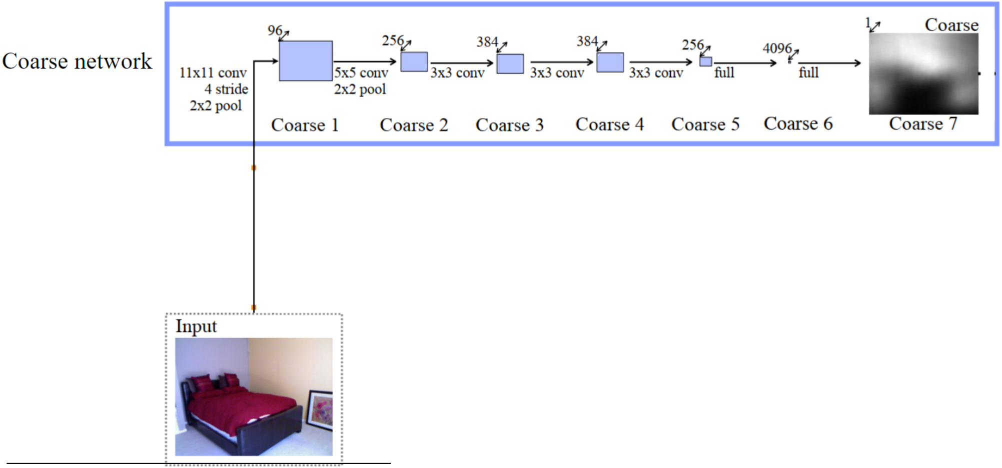

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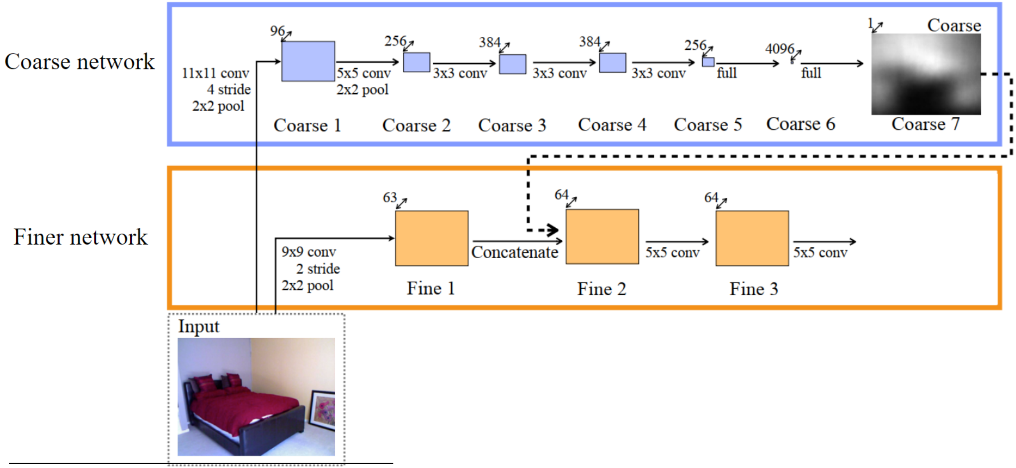

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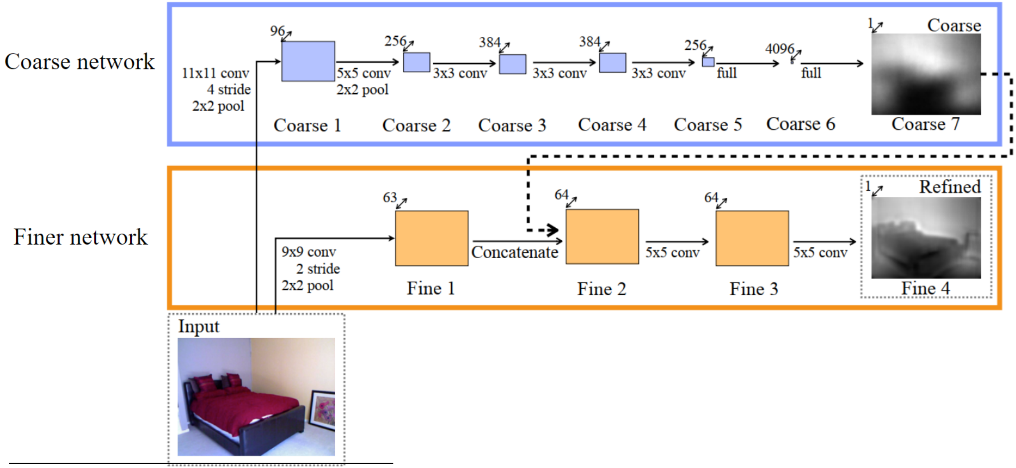

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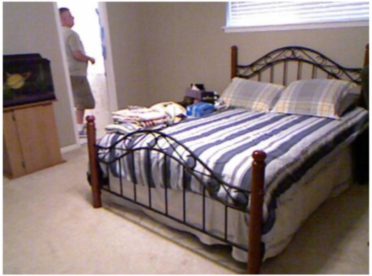
Depth Estimation from Single Image: Sample Results

Input



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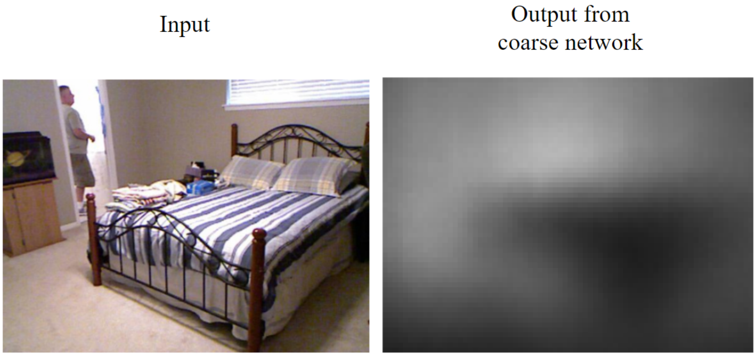

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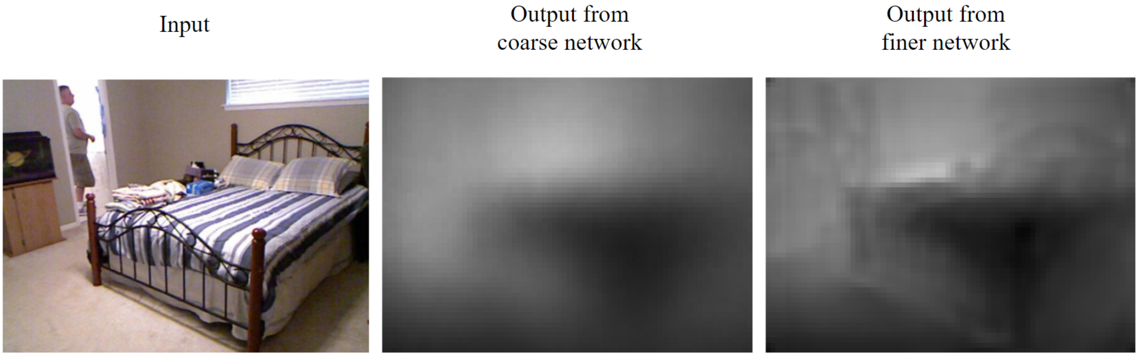

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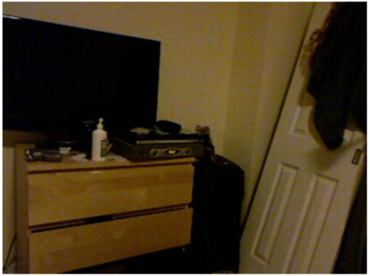

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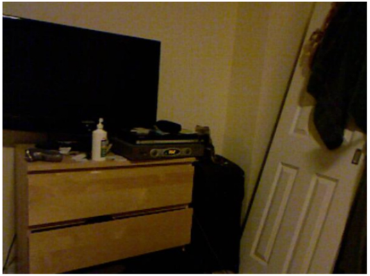
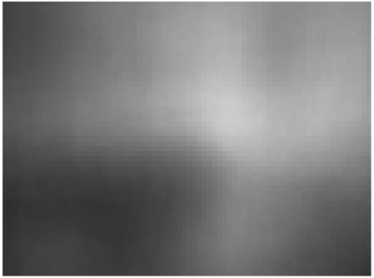


Output from
coarse network



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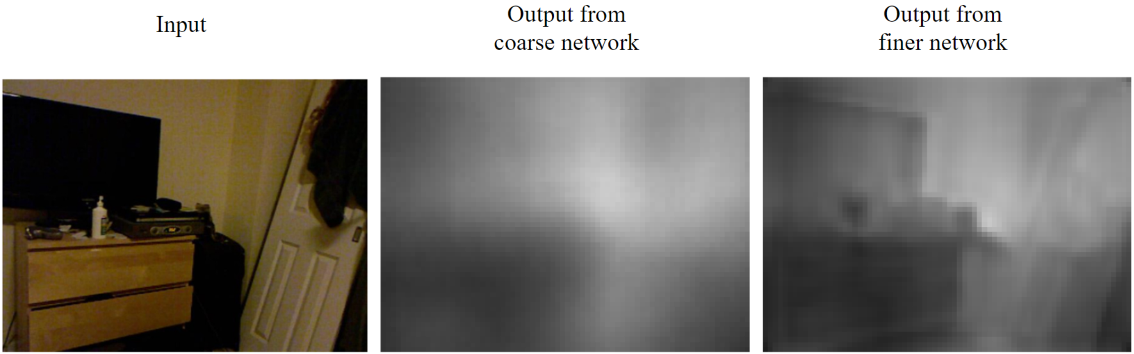

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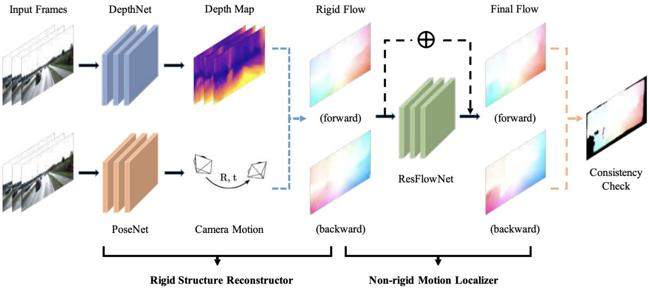
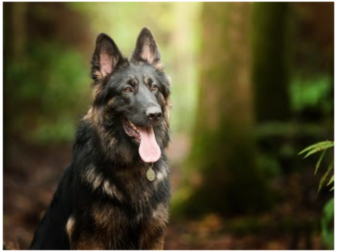
GeoNet[2]



Consists of rigid structure reconstructor for estimating static scene geometry and non-rigid motion localizer for capturing dynamic objects. Consistency check within any pair of bidirectional flow predictions is adopted for taking care of occlusions and non-Lambertian surfaces

[2]Yin and Shi, GeoNet: Unsupervised Learning of Dense Depth, Optical Flow and Camera Pose, CVPR 2018

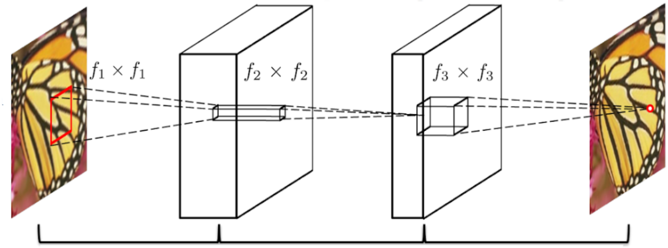
Super-resolution: Do you see a difference?



Super-resolution

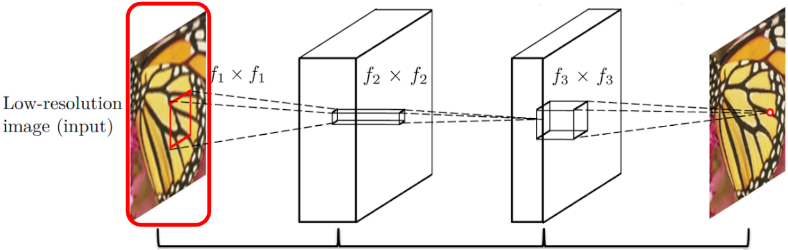
Credit: LG

Super-resolution using CNNs



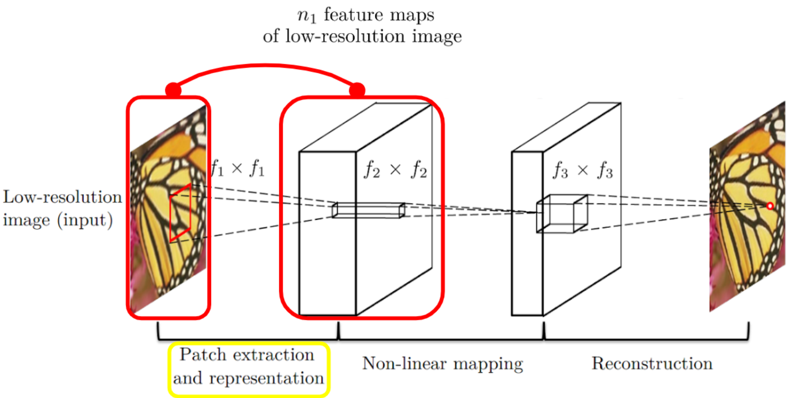
Credit: Dong, Chao, et al, Image Super-resolution using Deep Convolutional Networks, IEEE Trans on PAMI, 2015

Super-resolution using CNNs



$\mathbf{Y}$

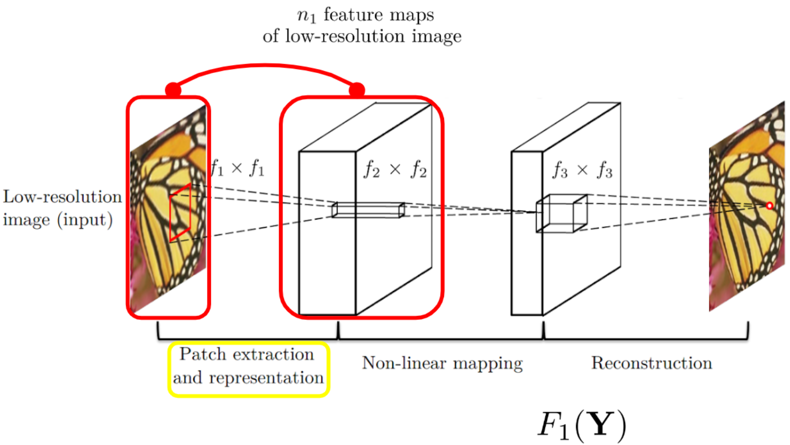
Credit: Dong, Chao, et al, Image Super-resolution using Deep Convolutional Networks, IEEE Trans on PAMI, 2015



$$F_1(\mathbf{Y}) = \max\left(0, W_1 * \mathbf{Y} + B_1\right)$$

Credit: Dong, Chao, et al, Image Super-resolution using Deep Convolutional Networks, IEEE Trans on PAMI, 2015

Super-resolution using CNNs



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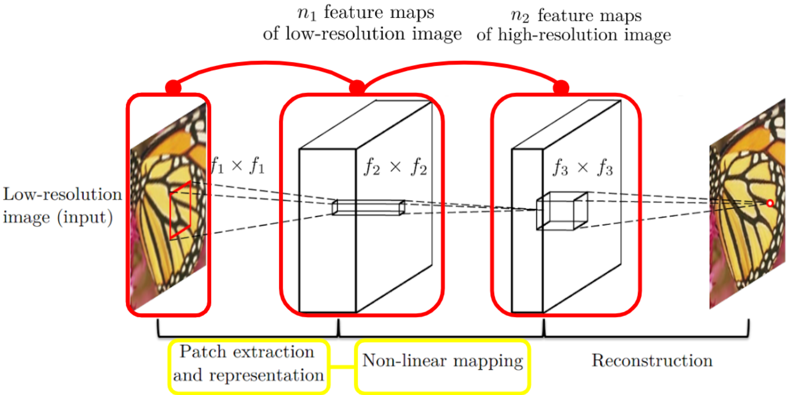
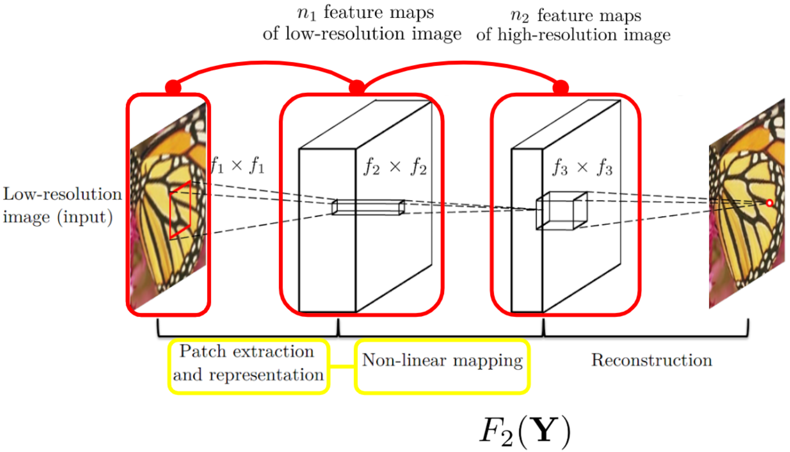


$$F_2(\mathbf{Y}) = \max\left(0, W_2 * F_1(\mathbf{Y}) + B_2\right)$$

Credit: Dong, Chao, et al, Image Super-resolution using Deep Convolutional Networks, IEEE Trans on PAMI, 2015

Super-resolution using CNNs



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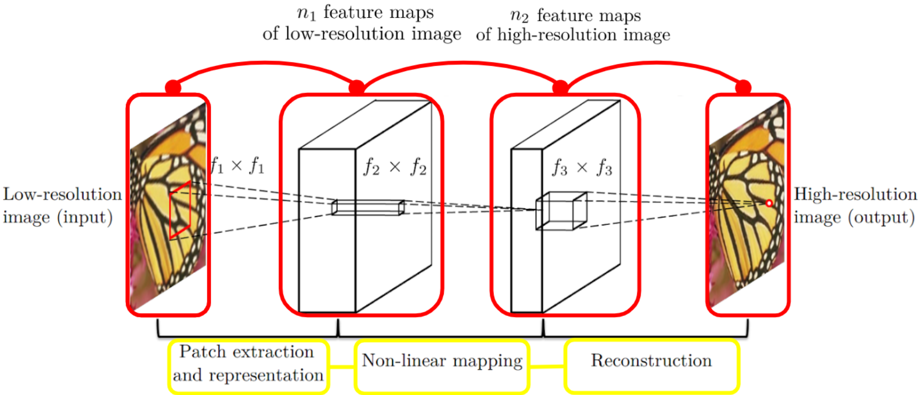

$$F(\mathbf{Y}) = W_3 * F_2(\mathbf{Y}) + B_3$$

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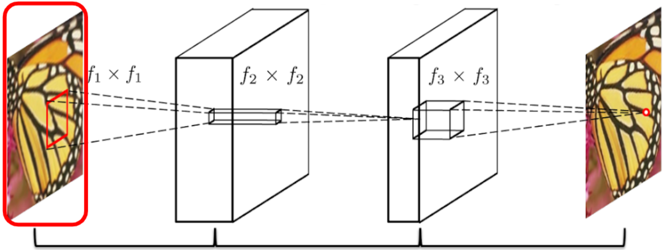

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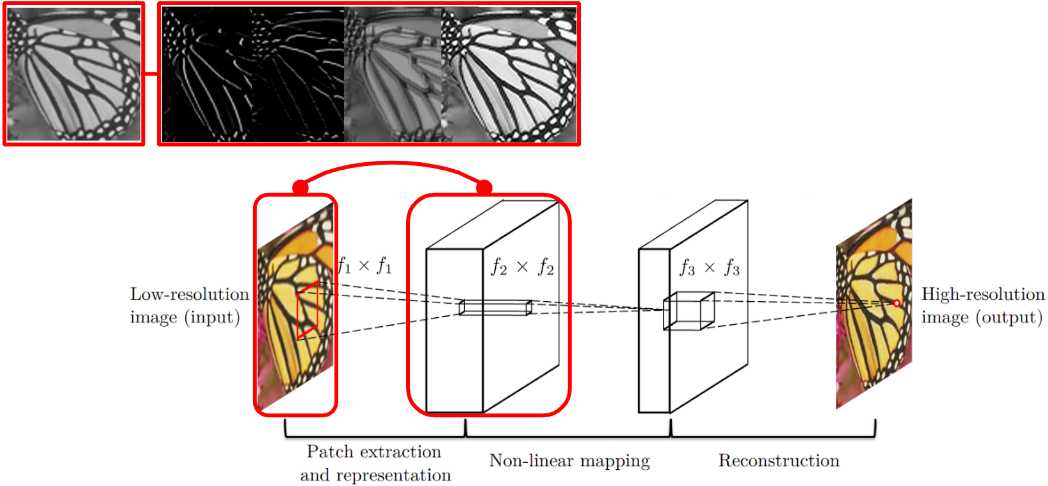

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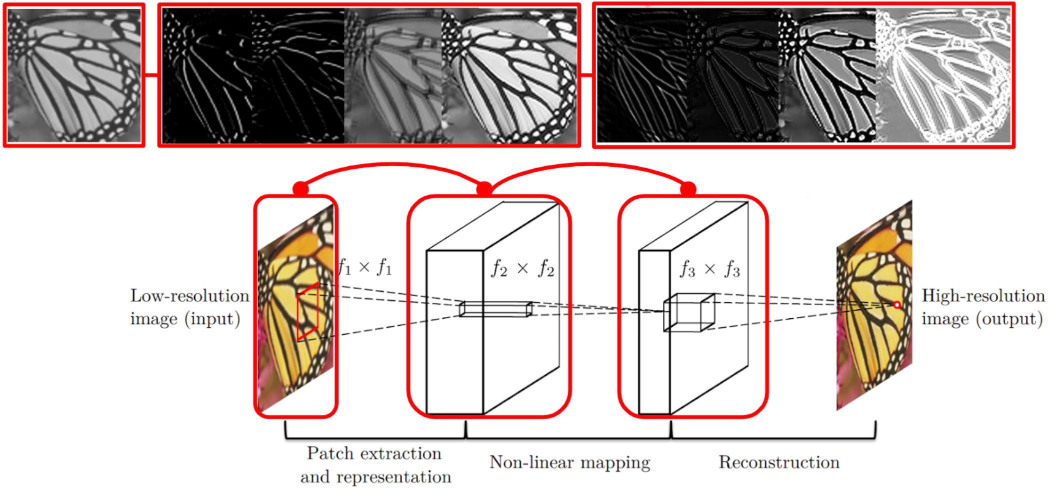

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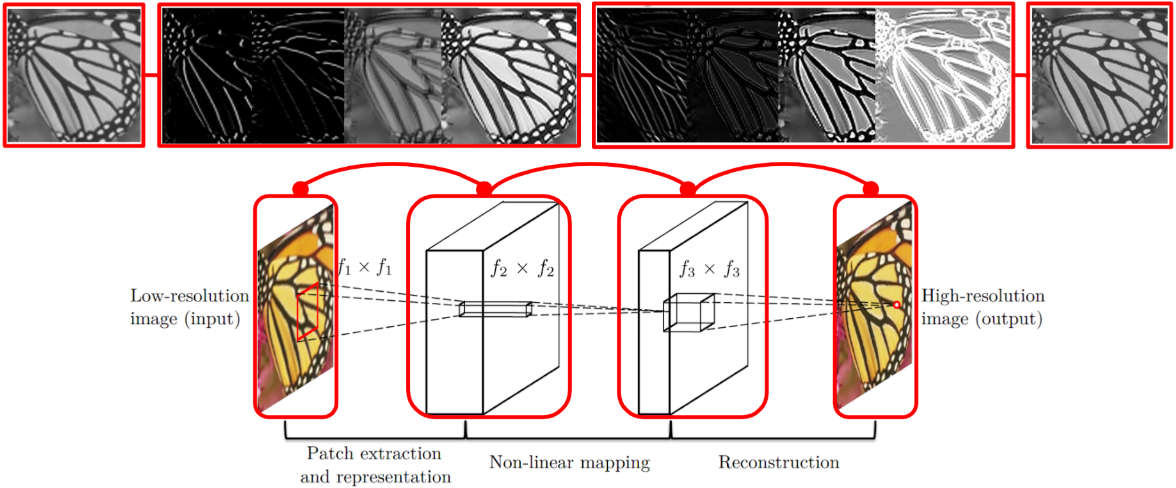

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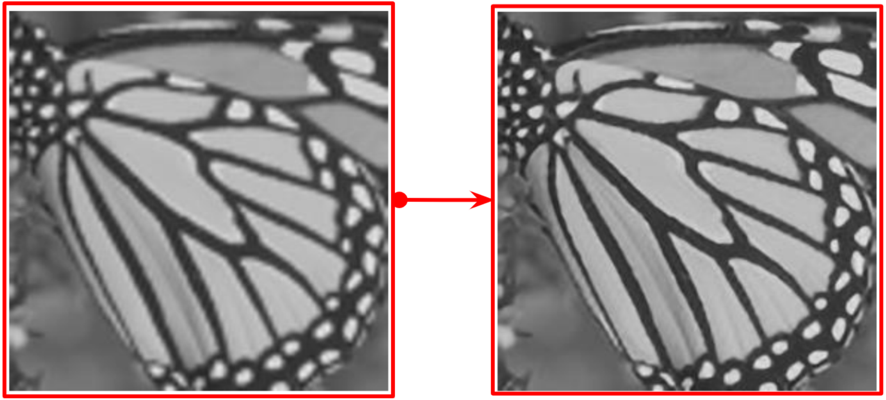

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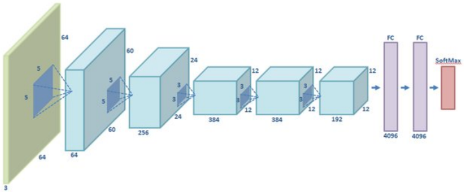
Anomaly Detection

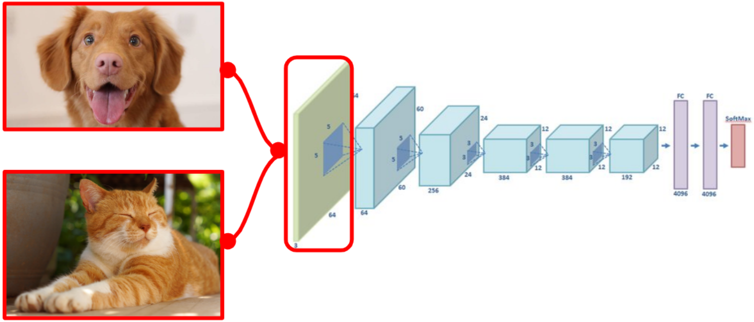
Find the odd one out:

- Table, Chair, Computer, Cupboard, Bed.
- Faraday, Newton, Edison, Beethoven.
- Pen, Calculator, Pencil, Ink.

Anomaly Detection

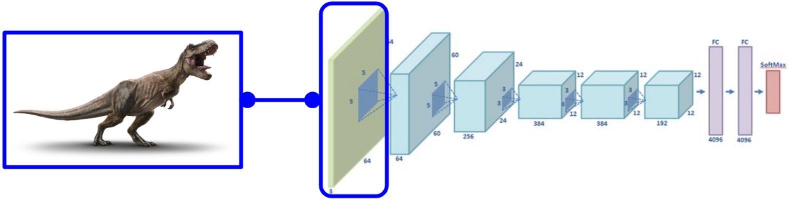


Anomaly Detection



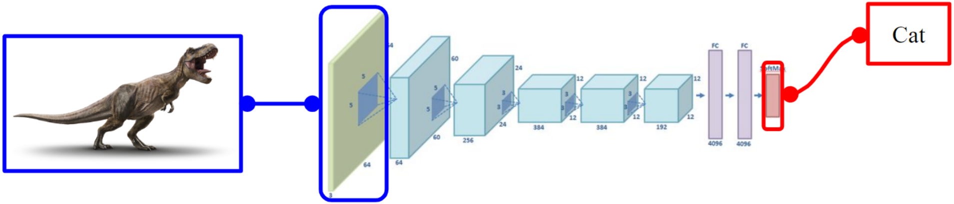
Train a network on cats and dogs

Anomaly Detection



During inference, provide the network
with an out of distribution image

Anomaly Detection



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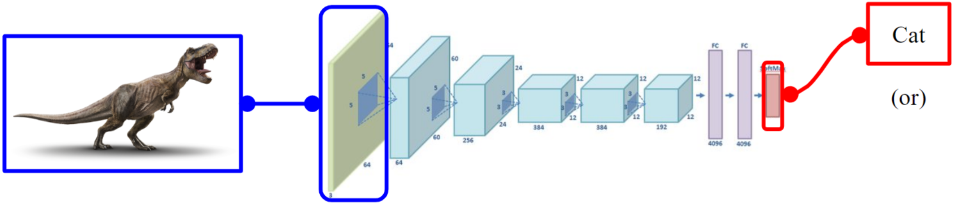

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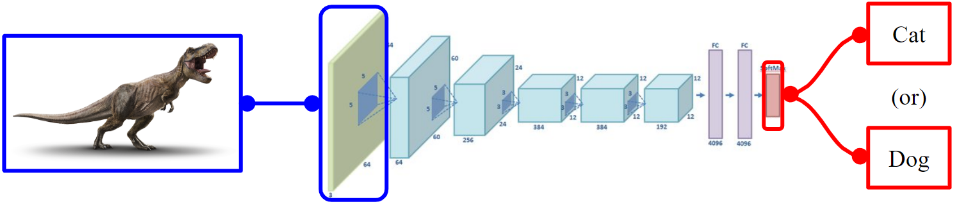

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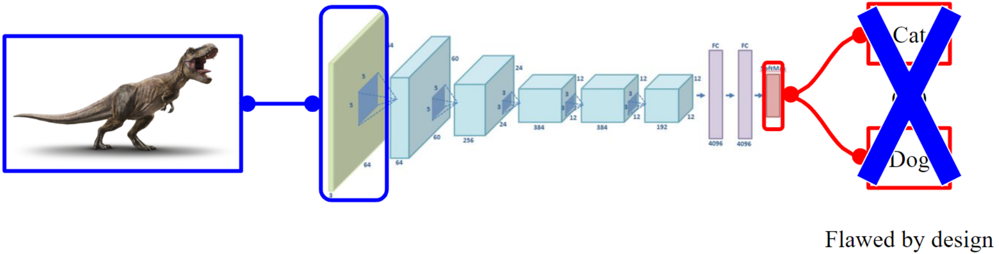
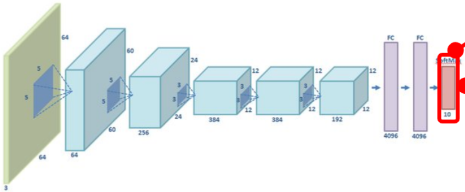


During inference, provide the network with an out of distribution image

Anomaly Detection

$$S_i(\boldsymbol{x};T) = \frac{\exp\left(f_i(\boldsymbol{x})\right)}{\sum_{j=1}^{N} \exp\left(f_j(\boldsymbol{x})\right)},$$



Anomaly Detection[3]

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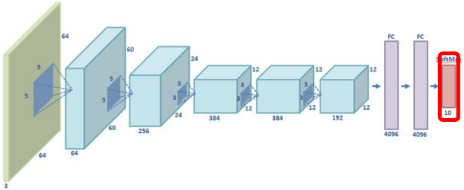
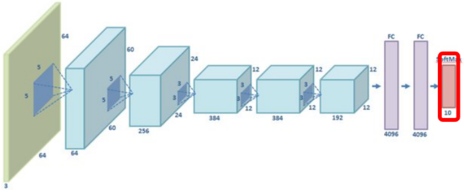


[3]Liang et al, Enhancing the Reliability of Out-of-distribution Image Detection in Neural Networks, ICLR 2018

Anomaly Detection[3]

$$S_i(\boldsymbol{x}; T) = \frac{\exp\left(f_i(\boldsymbol{x})/T\right)}{\sum_{j=1}^{N} \exp\left(f_j(\boldsymbol{x})/T\right)},$$



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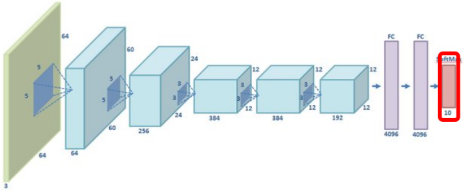

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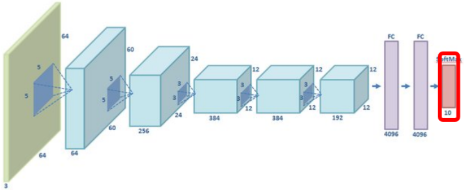

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$$\boxed{\tilde{\boldsymbol{x}} = \boldsymbol{x} - \varepsilon \text{sign}(-\nabla_{\boldsymbol{x}} \log S_{\hat{y}}(\boldsymbol{x};T))}$$

[3] Liang et al, Enhancing the Reliability of Out-of-distribution Image Detection in Neural Networks, ICLR 2018

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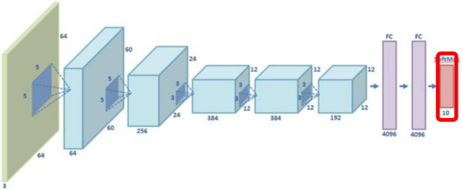

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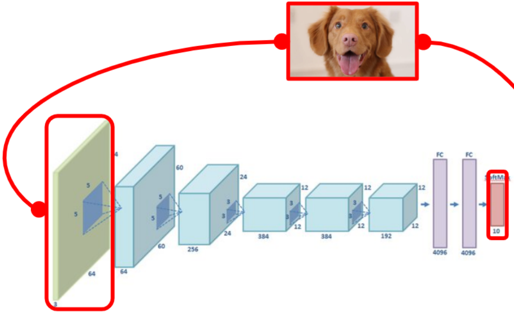

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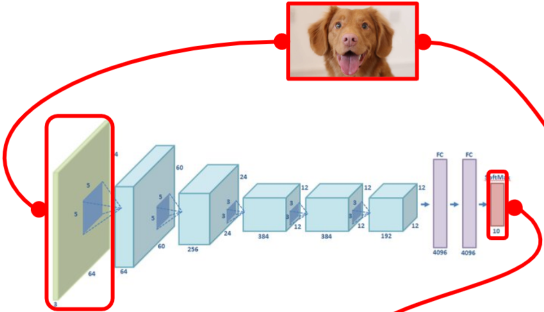

$$S_i(\boldsymbol{x};T) = \frac{\exp\left(f_i(\boldsymbol{x})/T\right)}{\sum_{j=1}^{N} \exp\left(f_j(\boldsymbol{x})/T\right)},$$

$$\tilde{\boldsymbol{x}} = \boldsymbol{x} - \varepsilon \operatorname{sign}(-\nabla_{\boldsymbol{x}} \log S_{\hat{y}}(\boldsymbol{x};T))$$

$$g(\boldsymbol{x};\delta,T,\varepsilon) = \begin{cases} 1 & \text{if} \max_i p(\tilde{\boldsymbol{x}};T) \leq \delta, \\ 0 & \text{if} \max_i p(\tilde{\boldsymbol{x}};T) > \delta. \end{cases}$$

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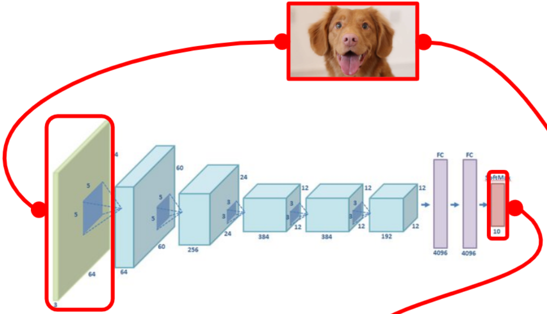

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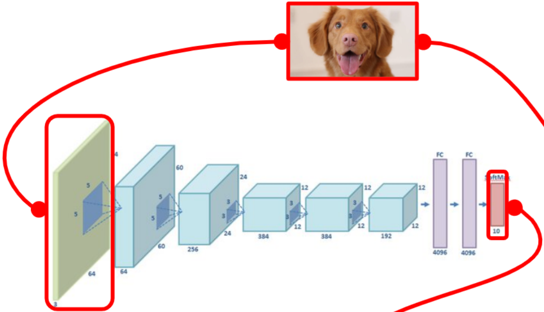

$$S_i(\boldsymbol{x};T) = \frac{\exp\left(f_i(\boldsymbol{x})/T\right)}{\sum_{j=1}^{N}\exp\left(f_j(\boldsymbol{x})/T\right)},$$

$$\tilde{\boldsymbol{x}} = \boldsymbol{x} - \varepsilon \text{sign}(-\nabla_{\boldsymbol{x}} \log S_{\hat{y}}(\boldsymbol{x};T))$$

$$g(\boldsymbol{x};\delta,T,\varepsilon) = \begin{cases} 1 & \text{if } \max_i p(\tilde{\boldsymbol{x}};T) \le \delta, \\ 0 & \text{if } \max_i p(\tilde{\boldsymbol{x}};T) > \delta. \end{cases}$$

in-distribution

out-of-distribution

[3] Liang et al, Enhancing the Reliability of Out-of-distribution Image Detection in Neural Networks, ICLR 2018

Homework

Readings

- Depth Estimation : https://paperswithcode.com/task/depth-estimation
- Super Resolution : https://paperswithcode.com/task/super-resolution
- Anomaly Detection : https://paperswithcode.com/task/anomaly-detection