# Deep Learning for the High Dynamic Range Imaging Pipeline

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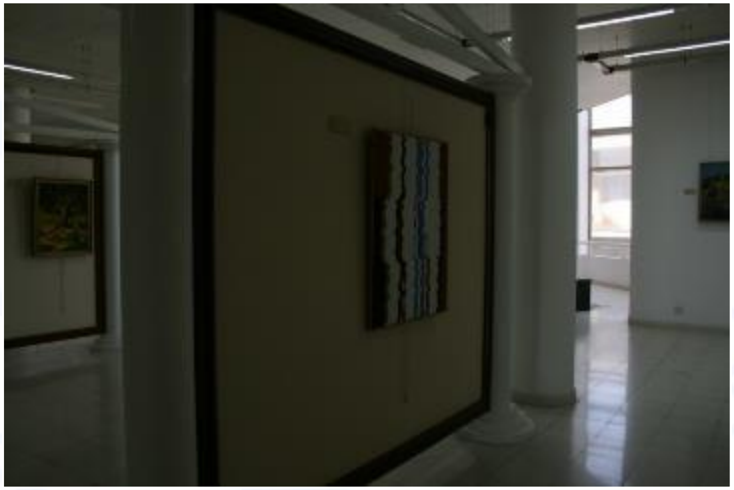
# Introduction to HDR

- Low/Standard Dynamic Range (LDR)
  - Limited Luminance range
  - Limited Colour gamut
  - 8 bit quantization [0-255]

- High Dynamic Range (HDR)
  - Real-World Lighting
  - 32-bit floats

# Introduction to HDR (2)

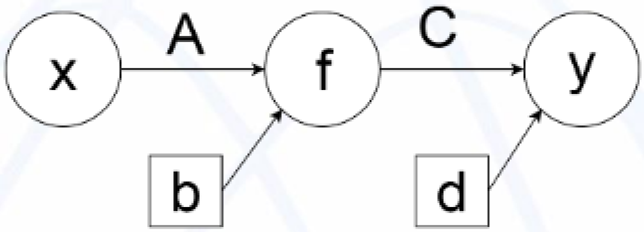
- ❑ Most content is LDR
- ❑ HDR → LDR straightforward (Tone Mapping)

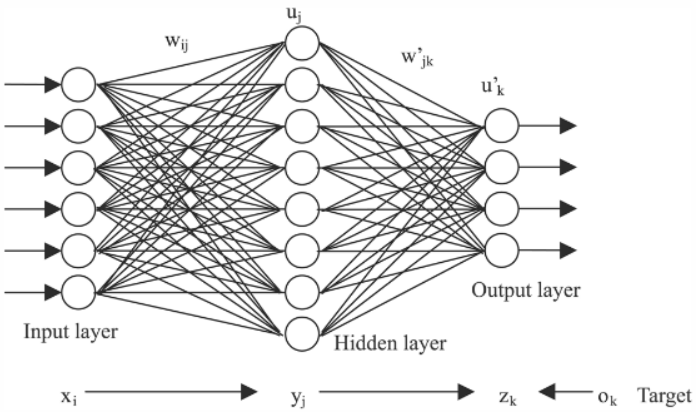

- ❑ Inverse is hard (LDR → HDR)
  - Expert knowledge / heuristics
  - Quantization, clipping
  - Non-linear local luminance shifts
- ❑ Proposed data-driven solution
  - Learn relevant information from data

# Artificial Neural Networks

- Single hidden layer

$$\boldsymbol{y} = C\boldsymbol{f}(A\boldsymbol{x} + \boldsymbol{b}) + \boldsymbol{d}$$



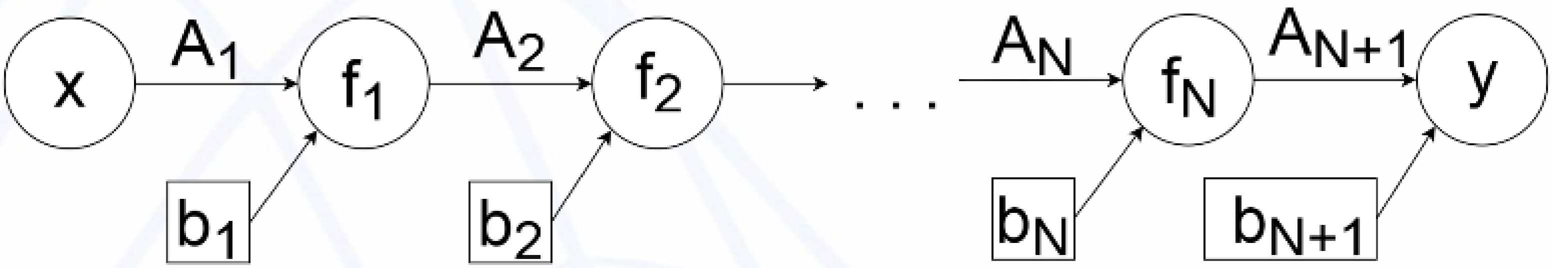

- Activations: Sigmoid, Tanh, Rectifiers (ReLU, PReLU, ELU, SELU) ...
- Find parameters that minimize some ‘loss’ between model and data
  - Euclidean distance (least squares regression)

$$\sum_i \|\bar{\boldsymbol{y}}_i - \boldsymbol{y}_i\|^2$$

- Stochastic Gradient Descent with Backpropagation

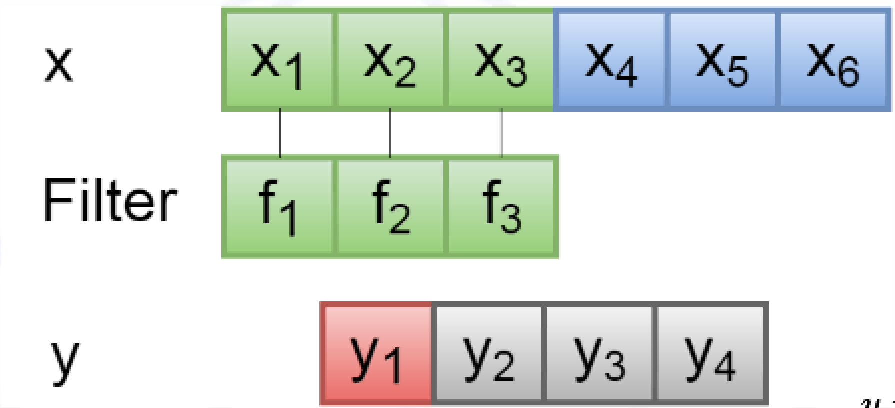
# Going Deeper

$$\boldsymbol{y} = A_{\boldsymbol{N+1}} \boldsymbol{f}_{\boldsymbol{N}}( A_{\boldsymbol{N}} \ldots \boldsymbol{f}_{\boldsymbol{2}}( A_{\boldsymbol{2}} \boldsymbol{f}_{\boldsymbol{1}}(A_{\boldsymbol{1}} \boldsymbol{x} + \boldsymbol{b}_{\boldsymbol{1}}) + \boldsymbol{b}_{\boldsymbol{2}}) \ldots + \boldsymbol{b}_{\boldsymbol{N}}) + \boldsymbol{b}_{\boldsymbol{N+1}}$$




- Depth
  - Exponentially more expressive with less parameters
  - Computationally more efficient
  - Aids generalization over memorization

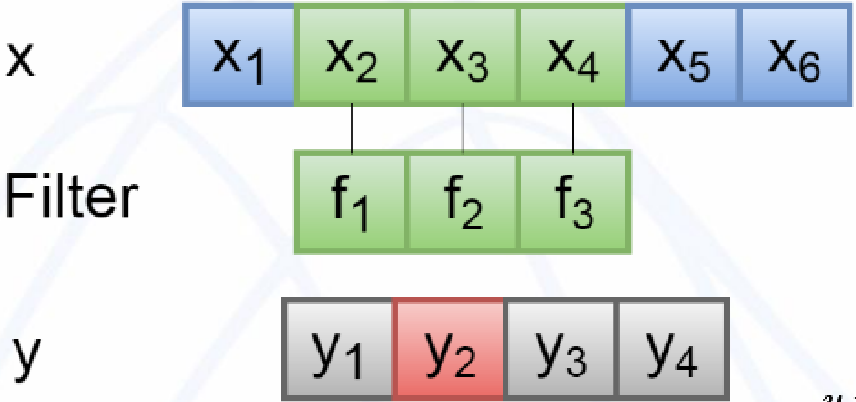
# Convolutions




$$y = h * x = \begin{bmatrix} h_1 & 0 & \dots & 0 & 0 \\ h_2 & h_1 & \dots & \vdots & \vdots \\ h_3 & h_2 & \dots & 0 & 0 \\ \vdots & h_3 & \dots & h_1 & 0 \\ h_{m-1} & \vdots & \dots & h_2 & h_1 \\ h_m & h_{m-1} & \vdots & \vdots & h_2 \\ 0 & h_m & \dots & h_{m-2} & \vdots \\ 0 & 0 & \dots & h_{m-1} & h_{m-2} \\ \vdots & \vdots & \vdots & h_m & h_{m-1} \\ 0 & 0 & 0 & \dots & h_m \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \\ x_3 \\ \vdots \\ x_n \end{bmatrix}$$

$$y_1 = x_1\ f_1 + x_2\ f_2 + x_3\ f_3$$

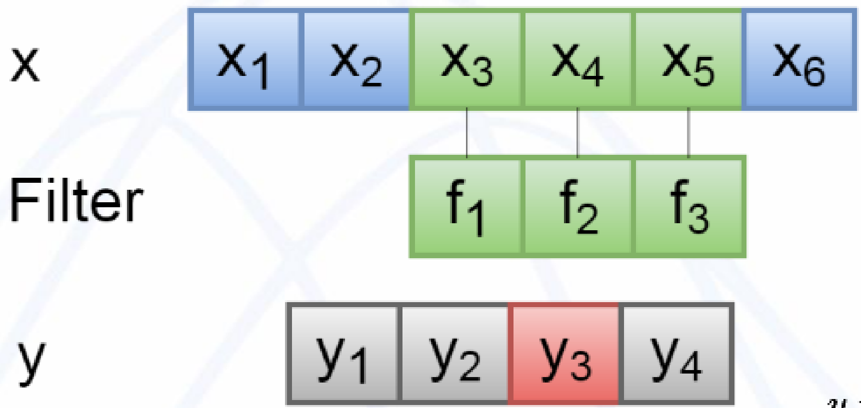
# Convolutions




$$y_2 = x_2\, f_1 + x_3\, f_2 + x_4\, f_3$$

$$y = h * x = \begin{bmatrix} h_1 & 0 & \dots & 0 & 0 \\ h_2 & h_1 & \dots & \vdots & \vdots \\ h_3 & h_2 & \dots & 0 & 0 \\ \vdots & h_3 & \dots & h_1 & 0 \\ h_{m-1} & \vdots & \dots & h_2 & h_1 \\ h_m & h_{m-1} & \vdots & \vdots & h_2 \\ 0 & h_m & \dots & h_{m-2} & \vdots \\ 0 & 0 & \dots & h_{m-1} & h_{m-2} \\ \vdots & \vdots & \vdots & h_m & h_{m-1} \\ 0 & 0 & 0 & \dots & h_m \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \\ x_3 \\ \vdots \\ x_n \end{bmatrix}$$

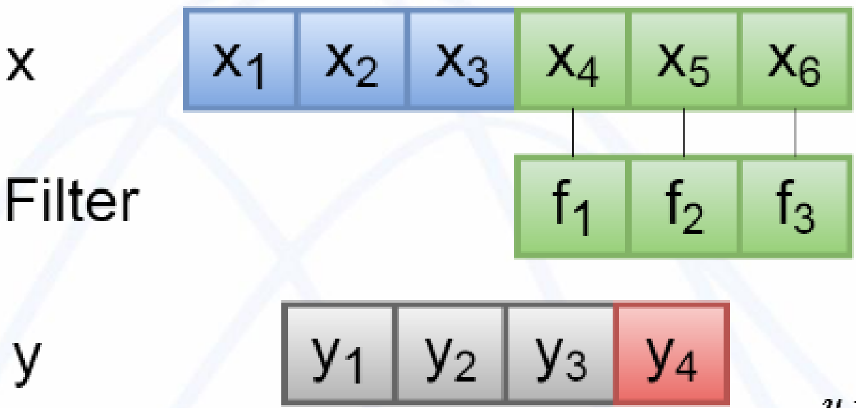
# Convolutions




$$y = h * x = \begin{bmatrix} h_1 & 0 & \dots & 0 & 0 \\ h_2 & h_1 & \dots & \vdots & \vdots \\ h_3 & h_2 & \dots & 0 & 0 \\ \vdots & h_3 & \dots & h_1 & 0 \\ h_{m-1} & \vdots & \dots & h_2 & h_1 \\ h_m & h_{m-1} & \vdots & \vdots & h_2 \\ 0 & h_m & \dots & h_{m-2} & \vdots \\ 0 & 0 & \dots & h_{m-1} & h_{m-2} \\ \vdots & \vdots & \vdots & h_m & h_{m-1} \\ 0 & 0 & 0 & \dots & h_m \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \\ x_3 \\ \vdots \\ x_n \end{bmatrix}$$

$$y_3 = x_3\ f_1 + x_4\ f_2 + x_5\ f_3$$

# Convolutions

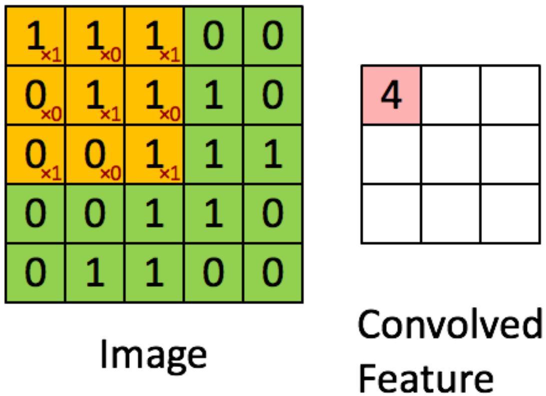



$$y = h * x = \begin{bmatrix} h_1 & 0 & \dots & 0 & 0 \\ h_2 & h_1 & \dots & \vdots & \vdots \\ h_3 & h_2 & \dots & 0 & 0 \\ \vdots & h_3 & \dots & h_1 & 0 \\ h_{m-1} & \vdots & \dots & h_2 & h_1 \\ h_m & h_{m-1} & \vdots & \vdots & h_2 \\ 0 & h_m & \dots & h_{m-2} & \vdots \\ 0 & 0 & \dots & h_{m-1} & h_{m-2} \\ \vdots & \vdots & \vdots & h_m & h_{m-1} \\ 0 & 0 & 0 & \dots & h_m \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \\ x_3 \\ \vdots \\ x_n \end{bmatrix}$$

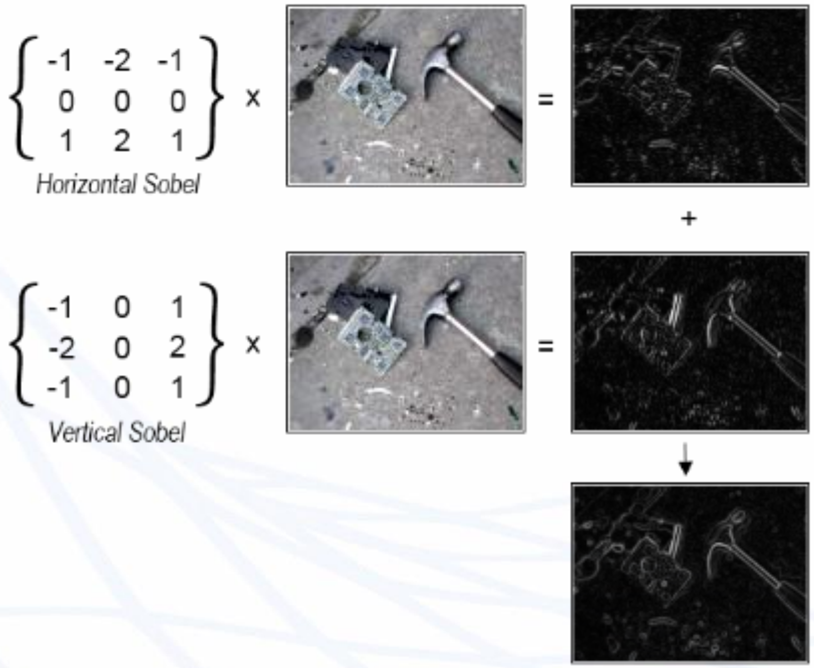
$$y_4 = x_4\, f_1 + x_5\, f_2 + x_6\, f_3$$

# Convolutions

- Likewise for 2D vectors (matrices, images)

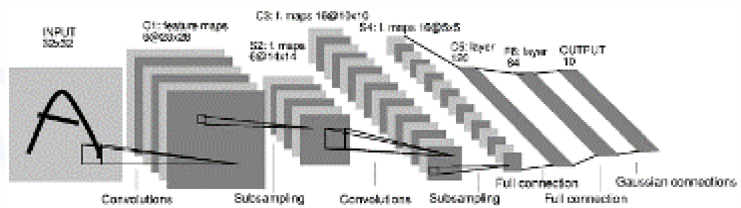



$$filter = \begin{bmatrix} 1 & 0 & 1 \\ 0 & 1 & 0 \\ 1 & 0 & 1 \end{bmatrix}$$



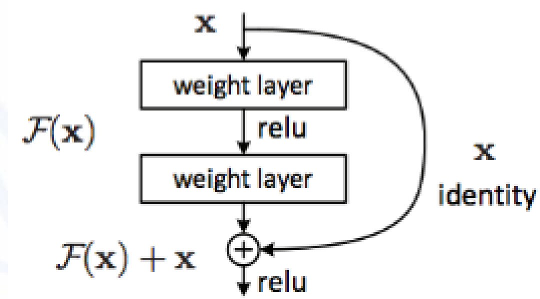
# Deep Convolutional Neural Networks

- Classification

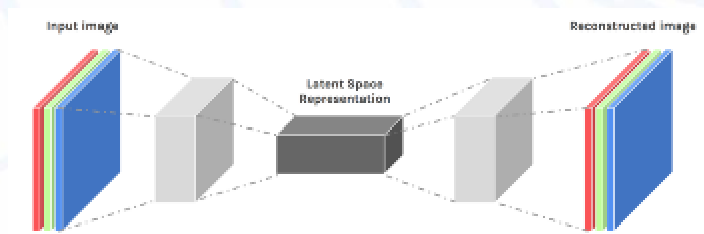



LeNet-5

- Modular improvements:
  - e.g. residual connections




- Auto-encoders



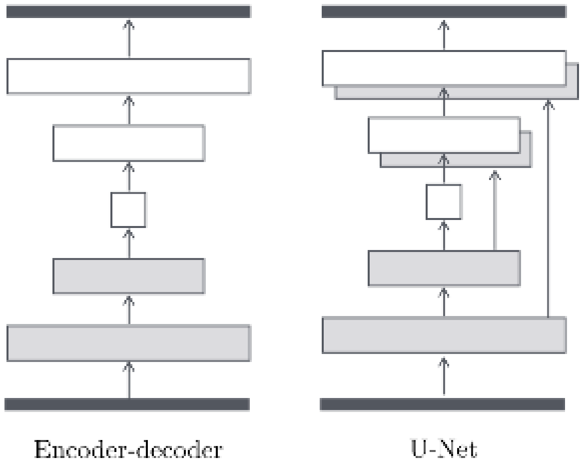
# Inverse problems in Imaging

Globally and Locally Consistent Image Completion
Iizuka et al., 2017

Colorful Image Colorization
Zhang et al., 2016

# Motivation for a new architecture

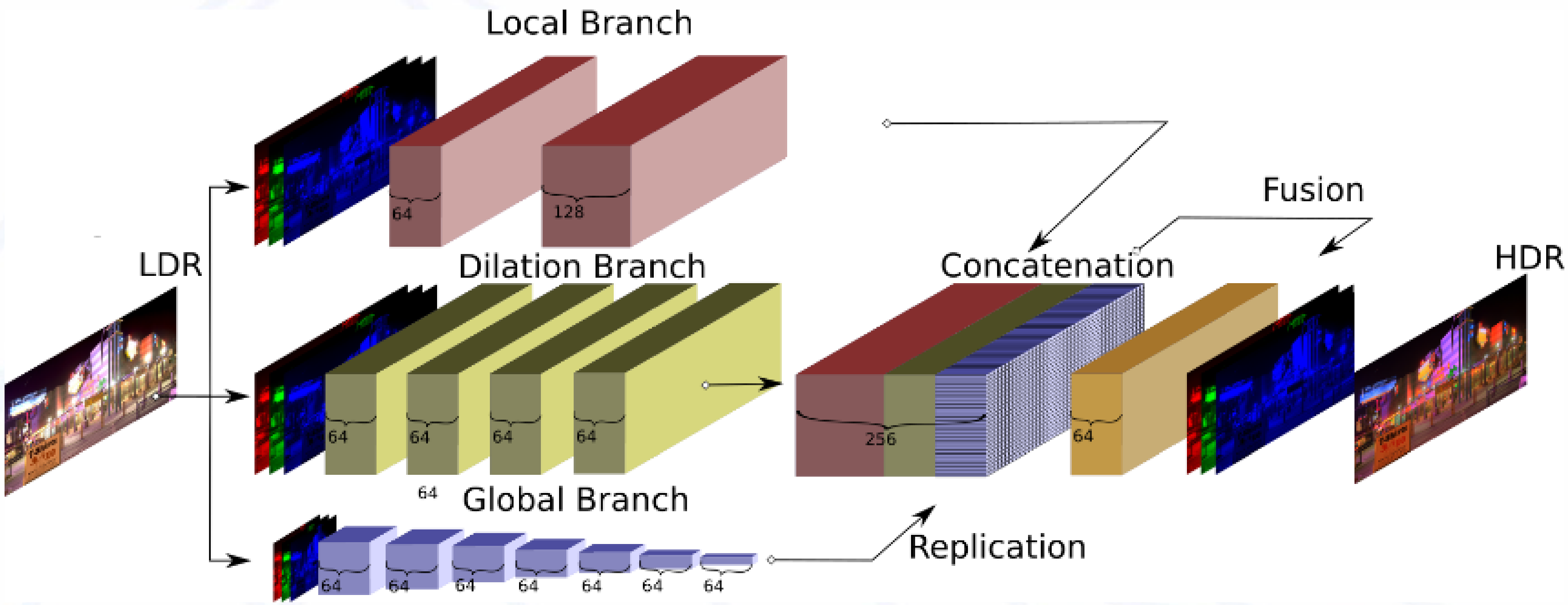
- UNet-like architectures:
  - Abstract representations
  - Multiscale context
  - However prone to artefacts
    - E.g. from the pix2pix Semantic Segmentation results



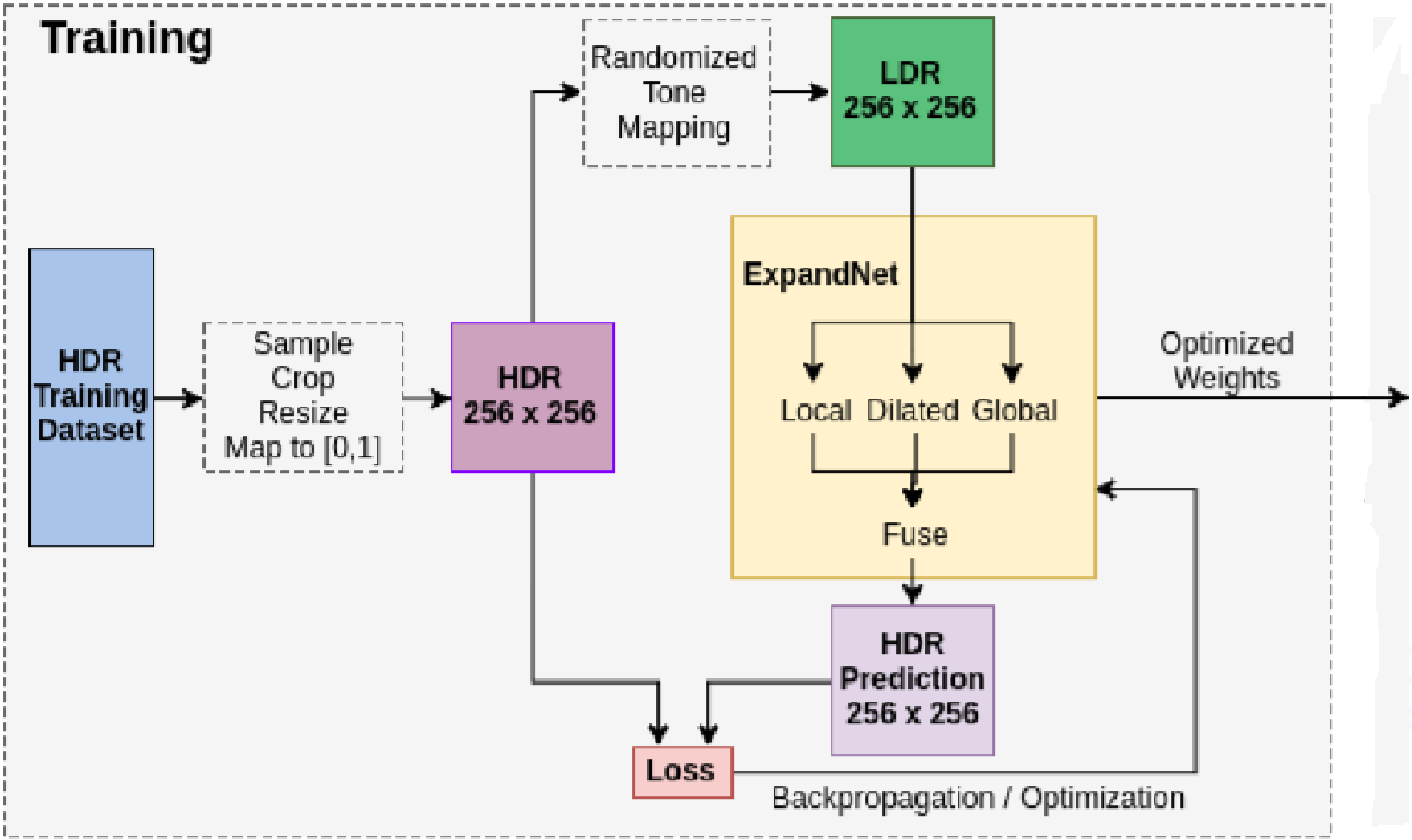


https://phillipi.github.io/pix2pix/images/cityscapes_cGAN_AtoB/latest_net_G_val/index.html

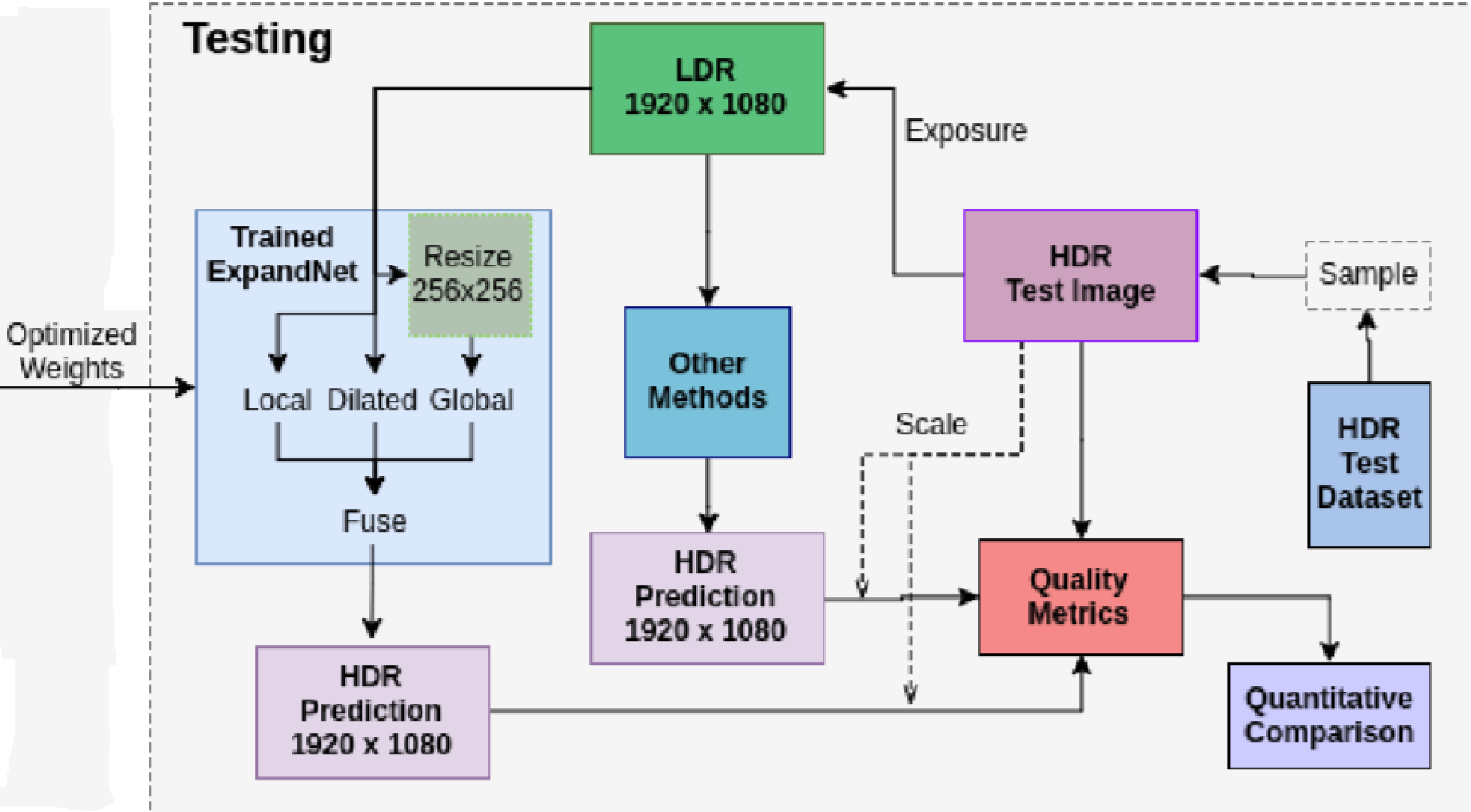
# ExpandNet


Local Branch
64
128
LDR
Dilation Branch
64
64
64
64
Concatenation
256
Fusion
64
HDR
64
Global Branch
64
64
64
64
64
64
64
Replication

# Workflow (training)

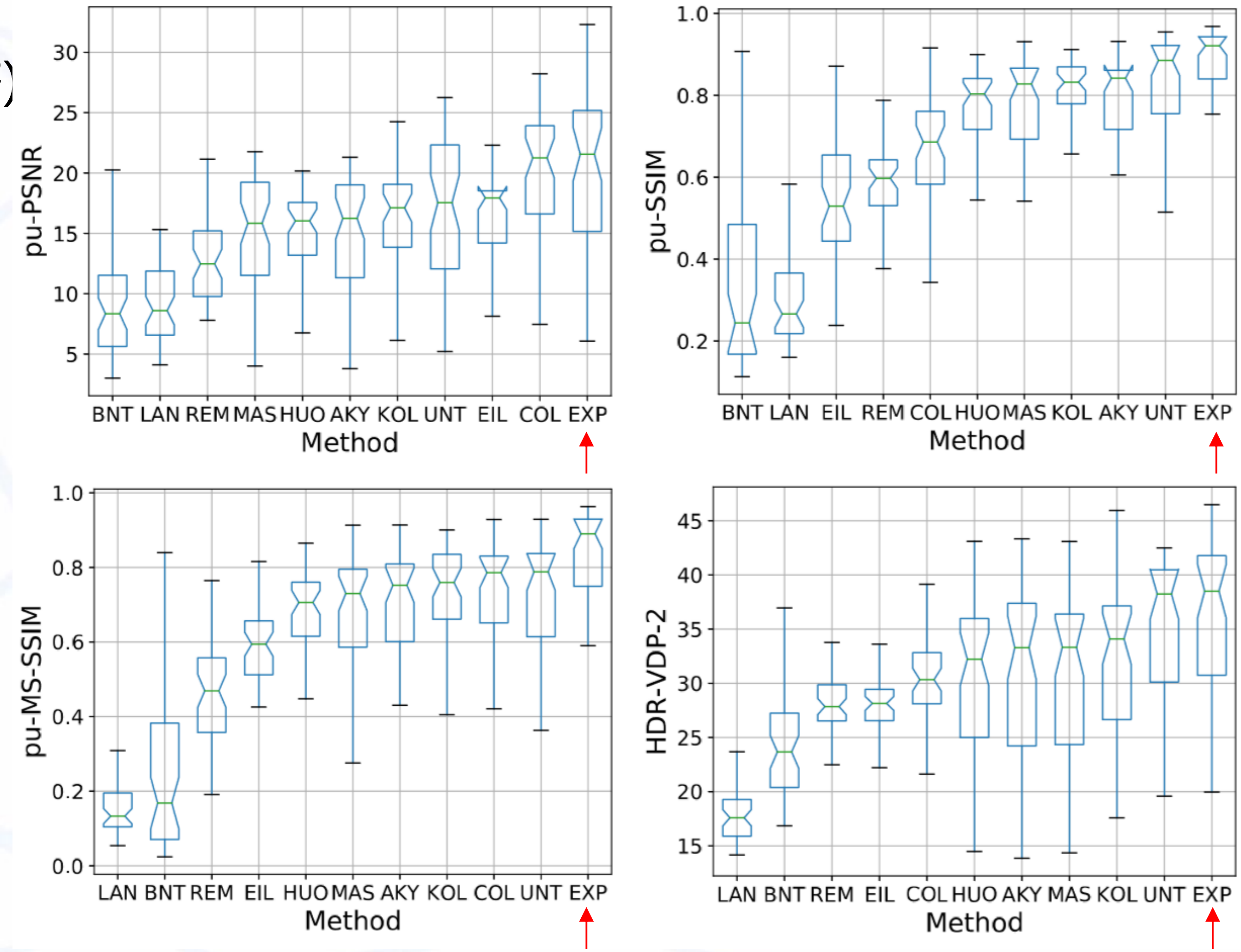


# Workflow (testing)



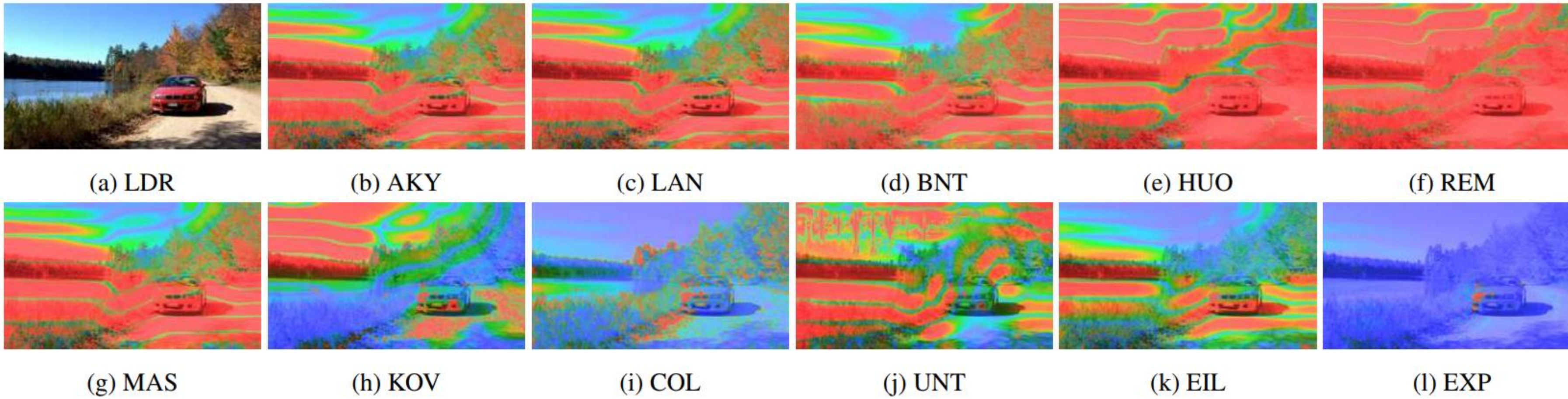
# Results

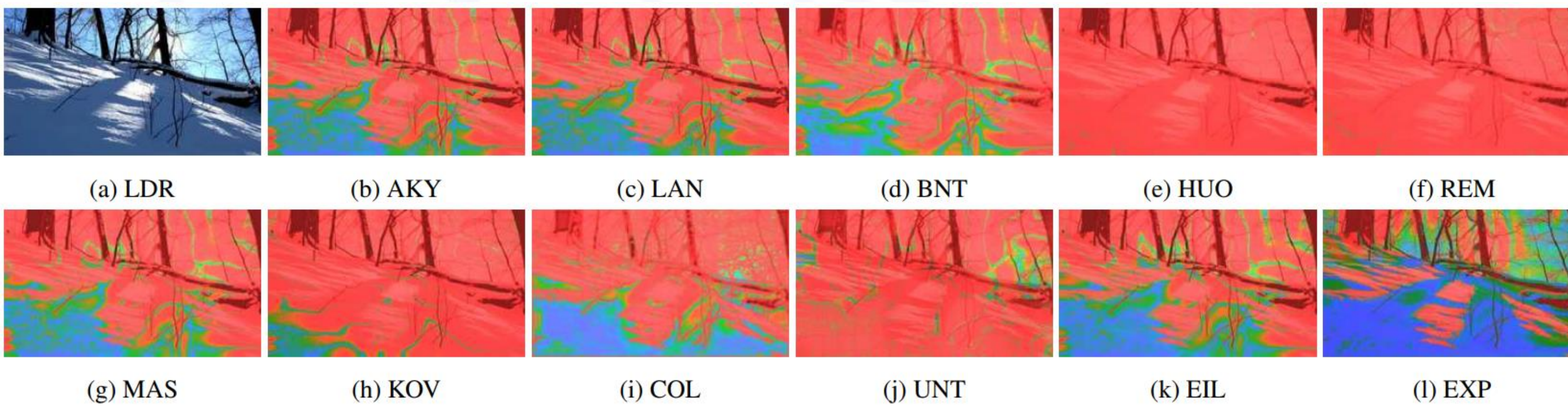
- 1000 nits (cd/m²)
  - PU-PSNR
  - PU-SSIM
  - PU-MSSSIM
  - HDR-VDP
- Significance
  - $p < 0.01$



# Results (2)

- HDR-VDP-2 – Detection Probability Maps



# Results (3)

- Image comparisons with other CNNs

(a) Input LDR (culling)

(b) UNT

(c) COL

(d) Exposure of original HDR

(e) EIL

(f) EXP

# Branches

All branches

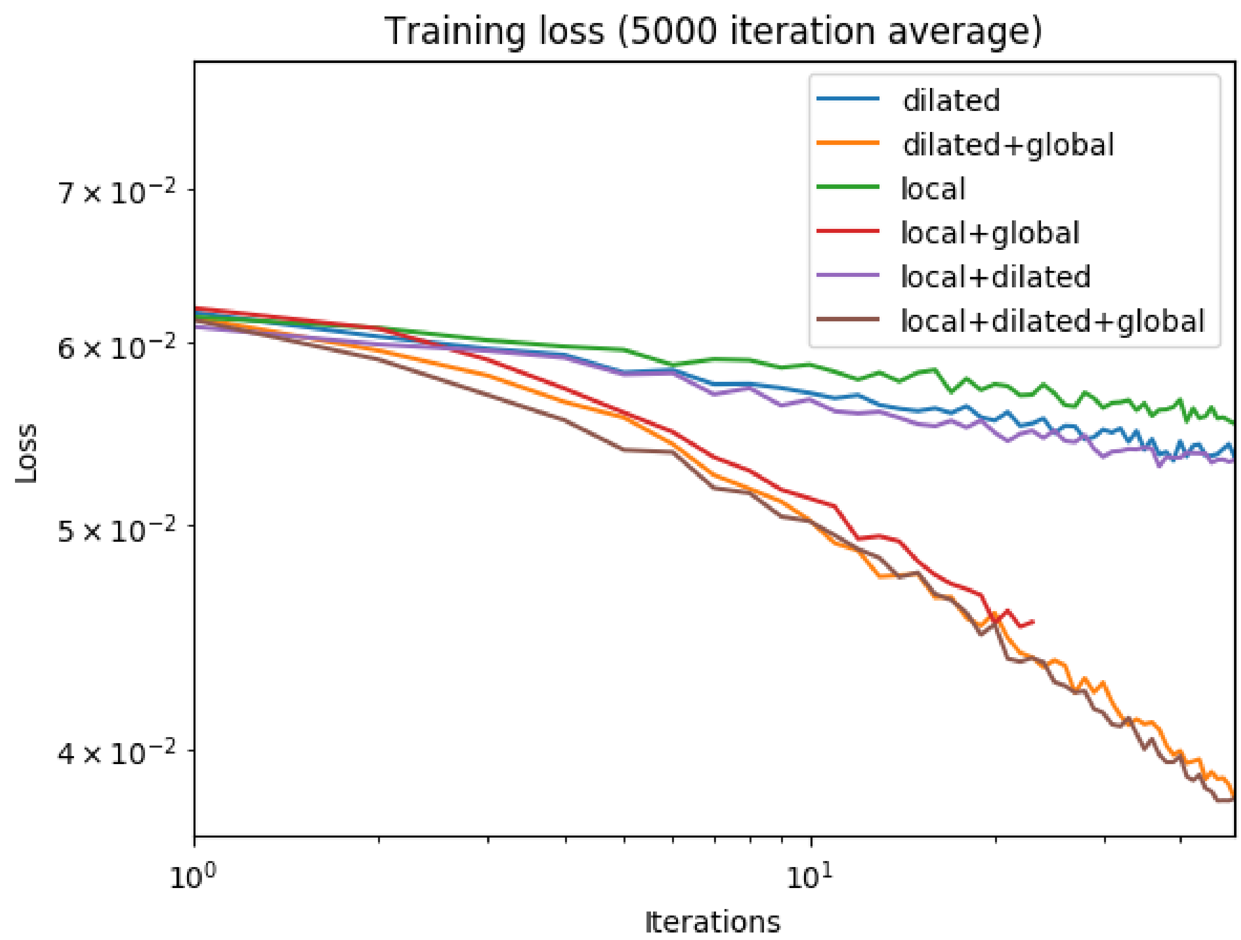


Local (masked D + G)


Dilated (masked L + G)

# Branches (2)

- Training combinations of branches



# Future Work

- Reducing compression artefacts
- Hallucinate under/over exposed regions
  - Generative Adversarial Networks (GANs)
- HDR Super-resolution
- LDR to HDR Video
  - Recurrent Neural Networks

# Thank you!

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