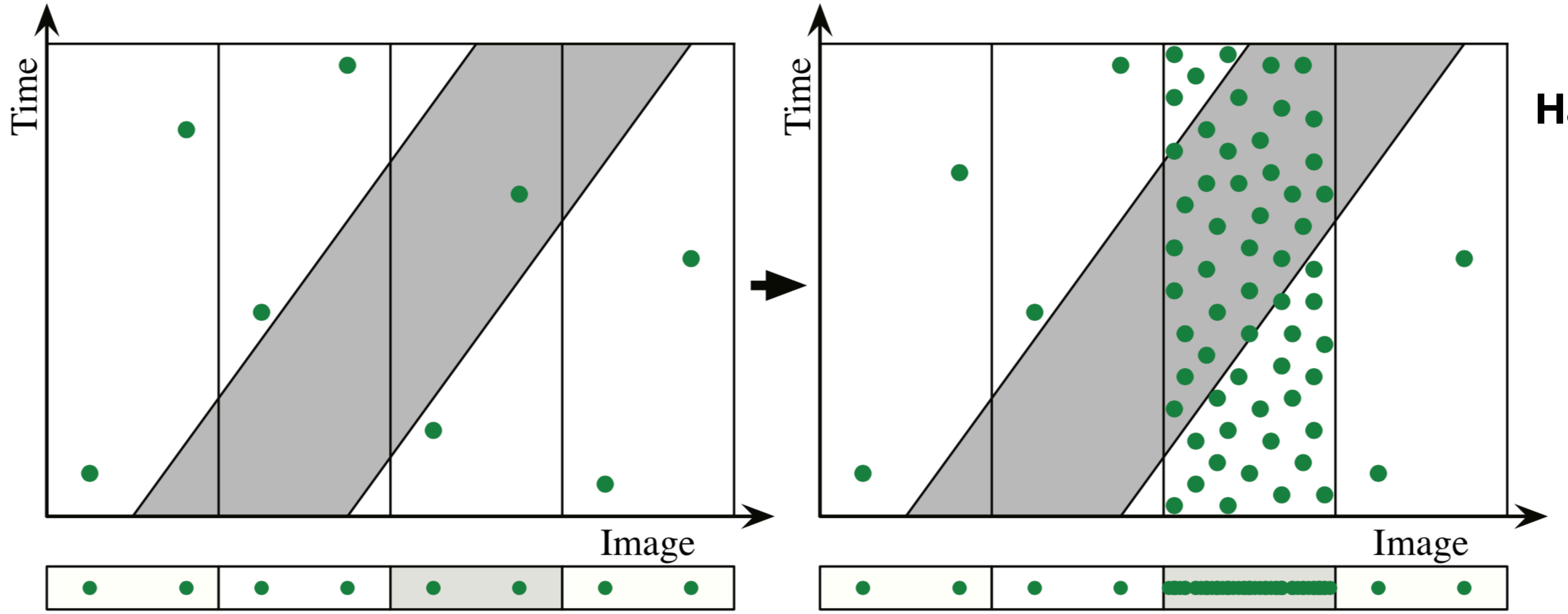
Denoising Algorithms: Path to Neural Networks I

Image courtesy Bako et al. [2017]

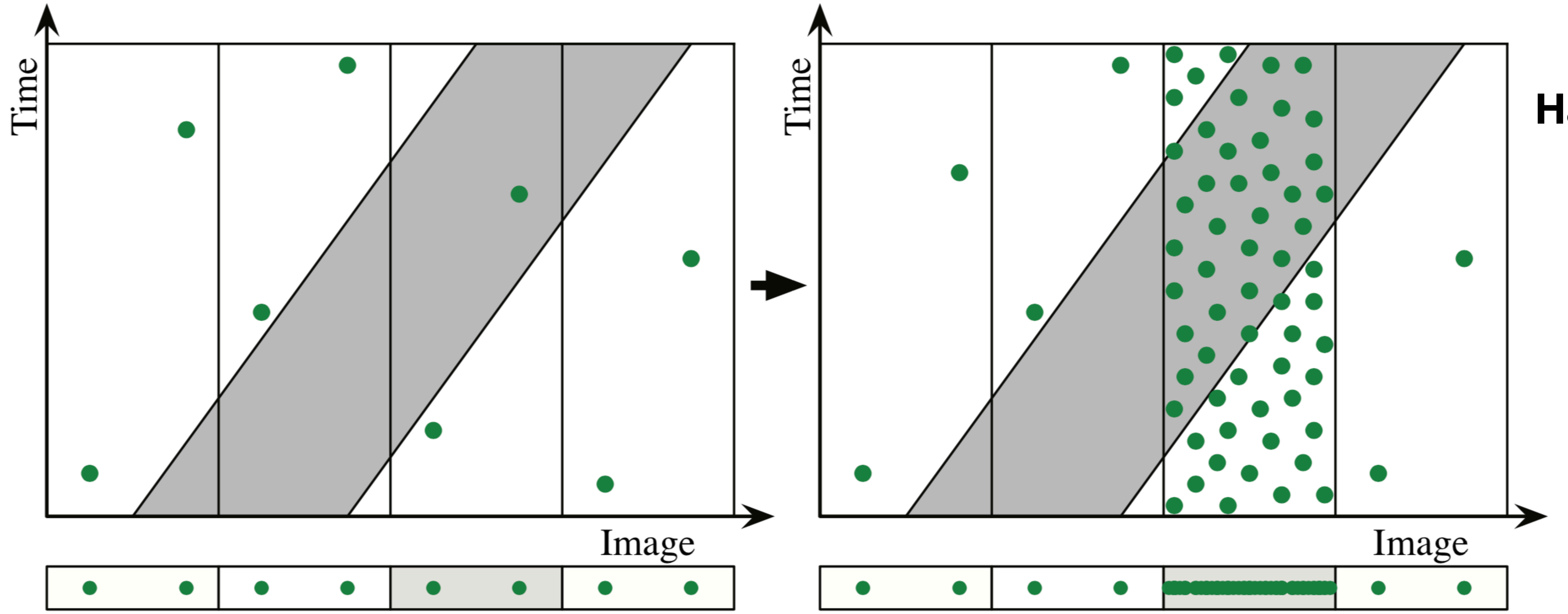
Recap:
Reconstruction using Spatio-temporal Sampling

Image-space Adaptive Sampling



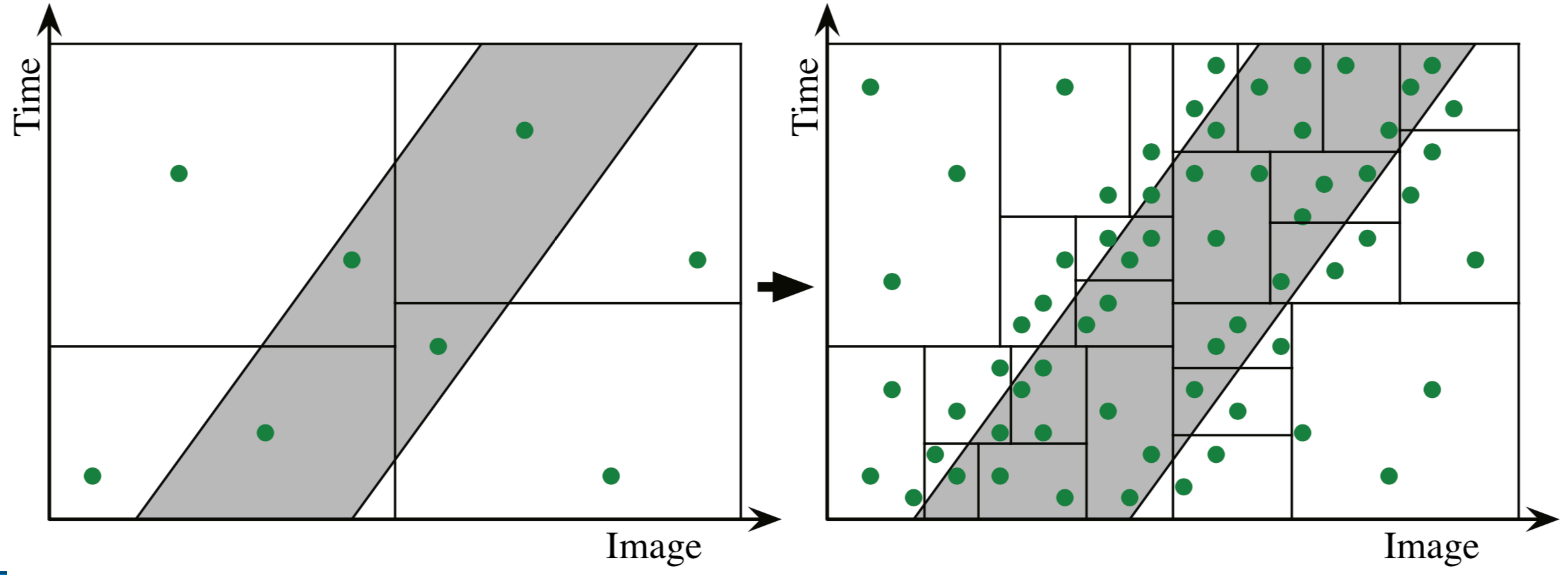
Hachisuka et al. [2008]

Image-space Adaptive Sampling

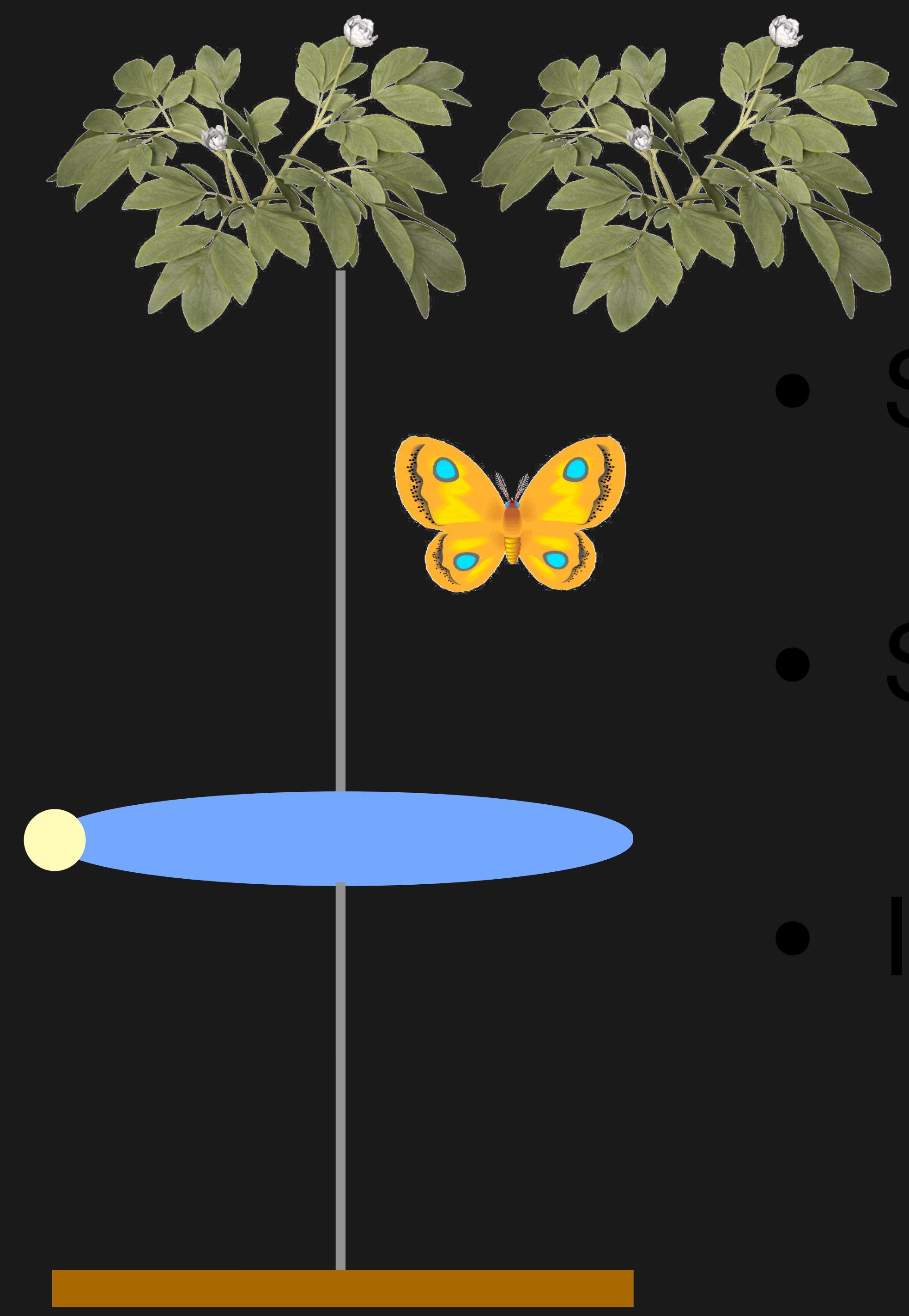


Hachisuka et al. [2008]

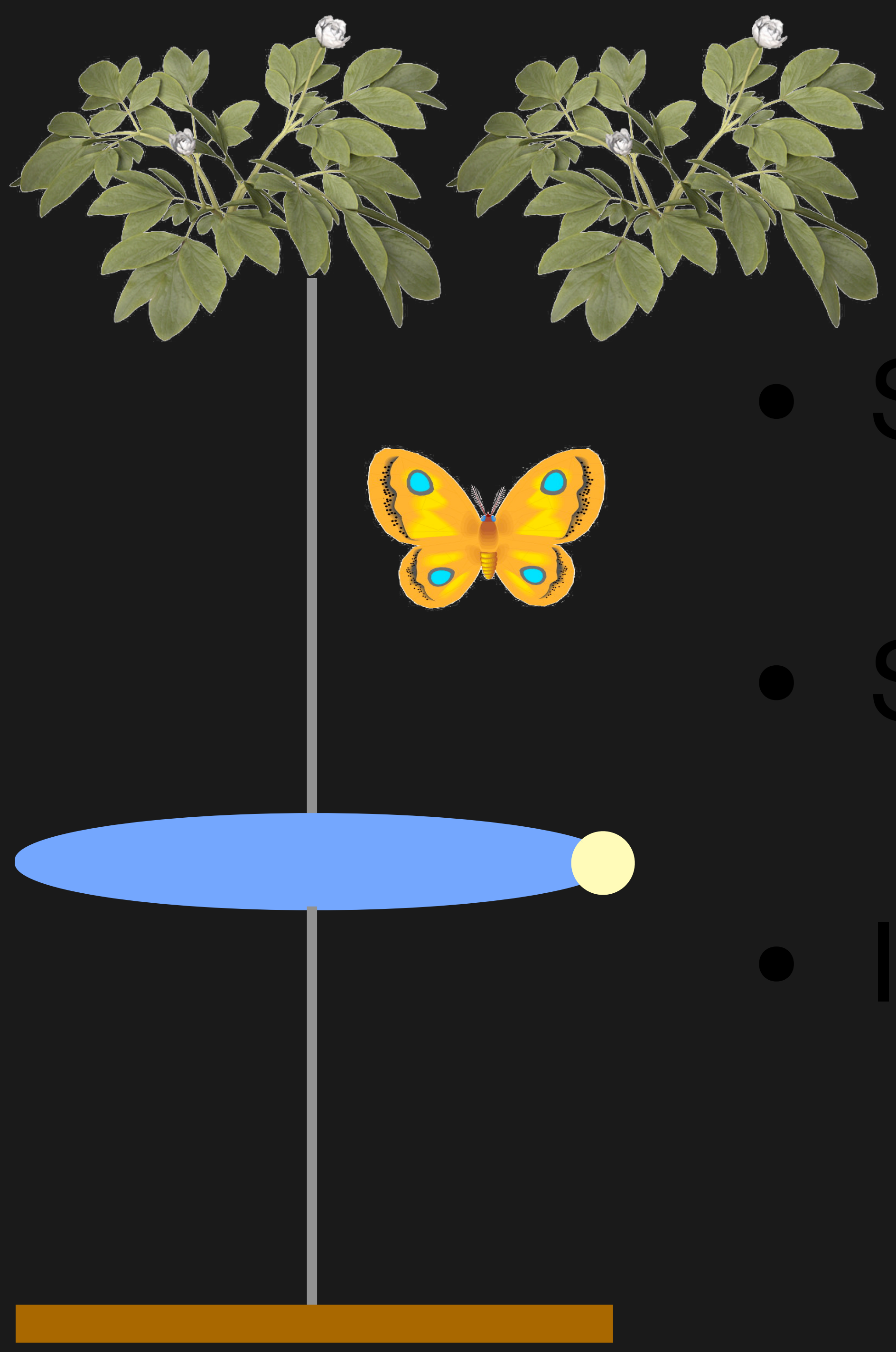
Multidimensional Adaptive Sampling



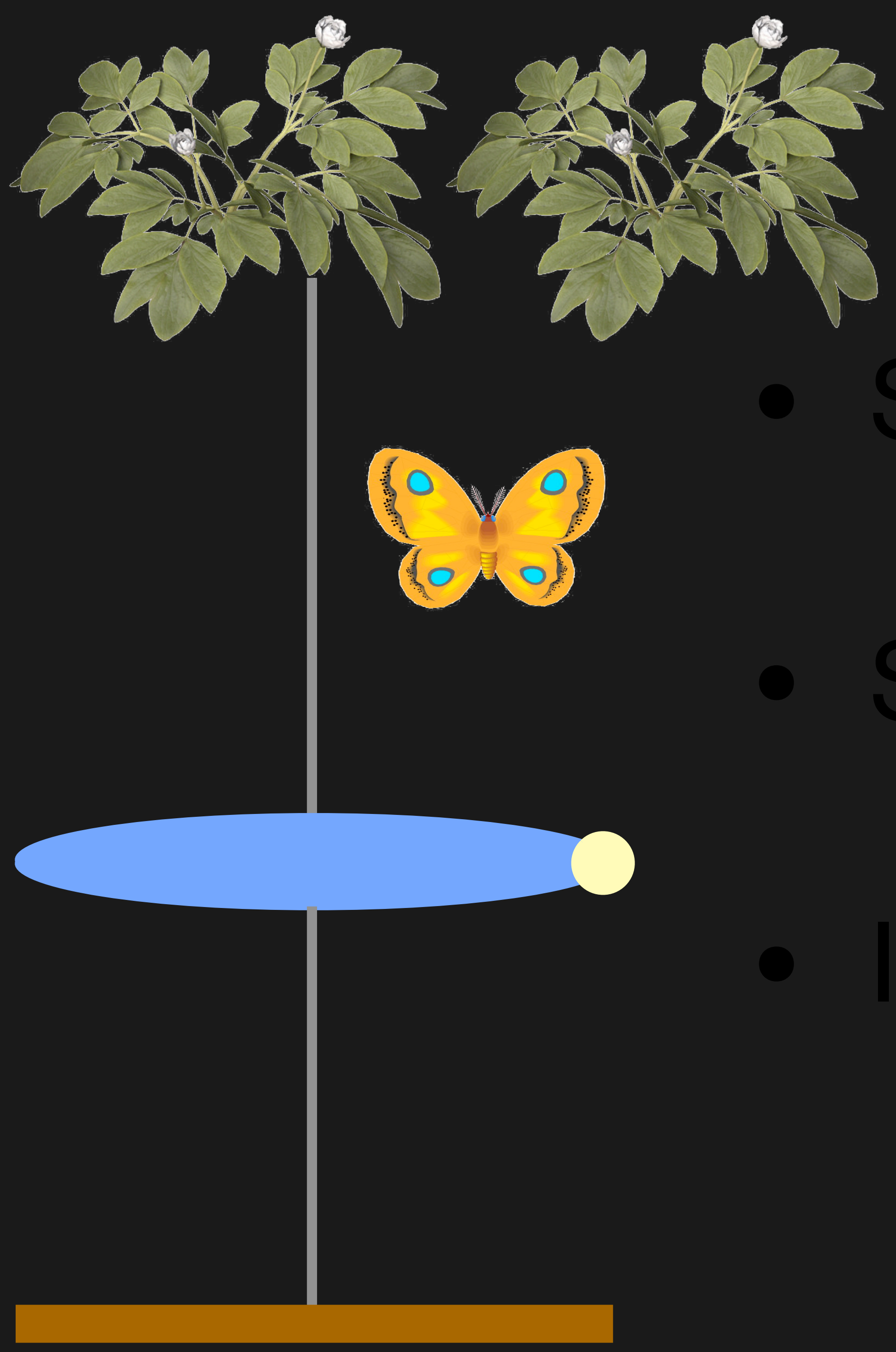
Depth of field



Depth of field



Depth of field




Slide from Jakko Lehtinen


1 scanline
Slide from Jakko Lehtinen


Slide from Jakko Lehtinen

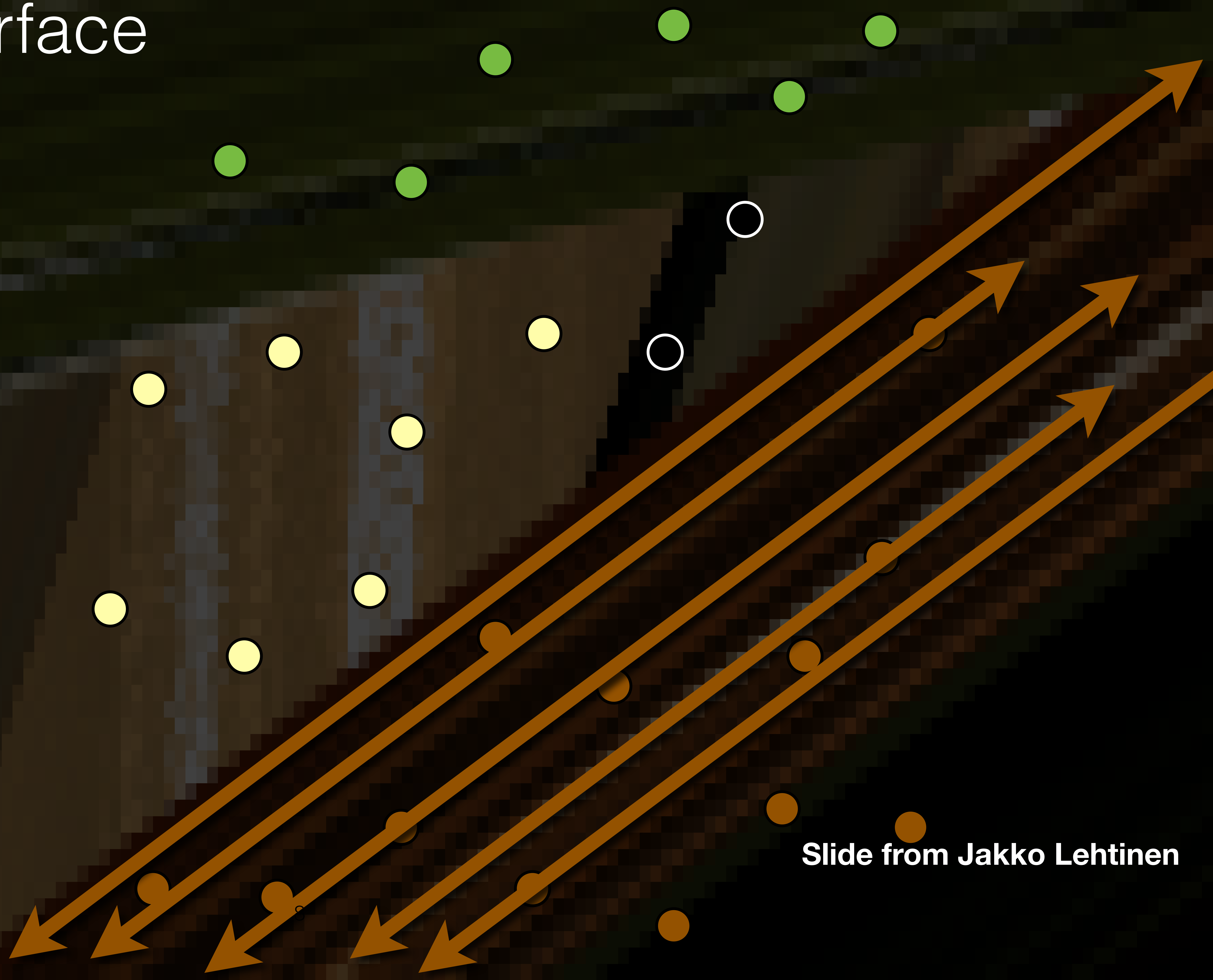

Slide from Jakko Lehtinen
Screen x


Lens u
Screen x
Slide from Jakko Lehtinen

Visibility: SameSurface

Slide from Jakko Lehtinen

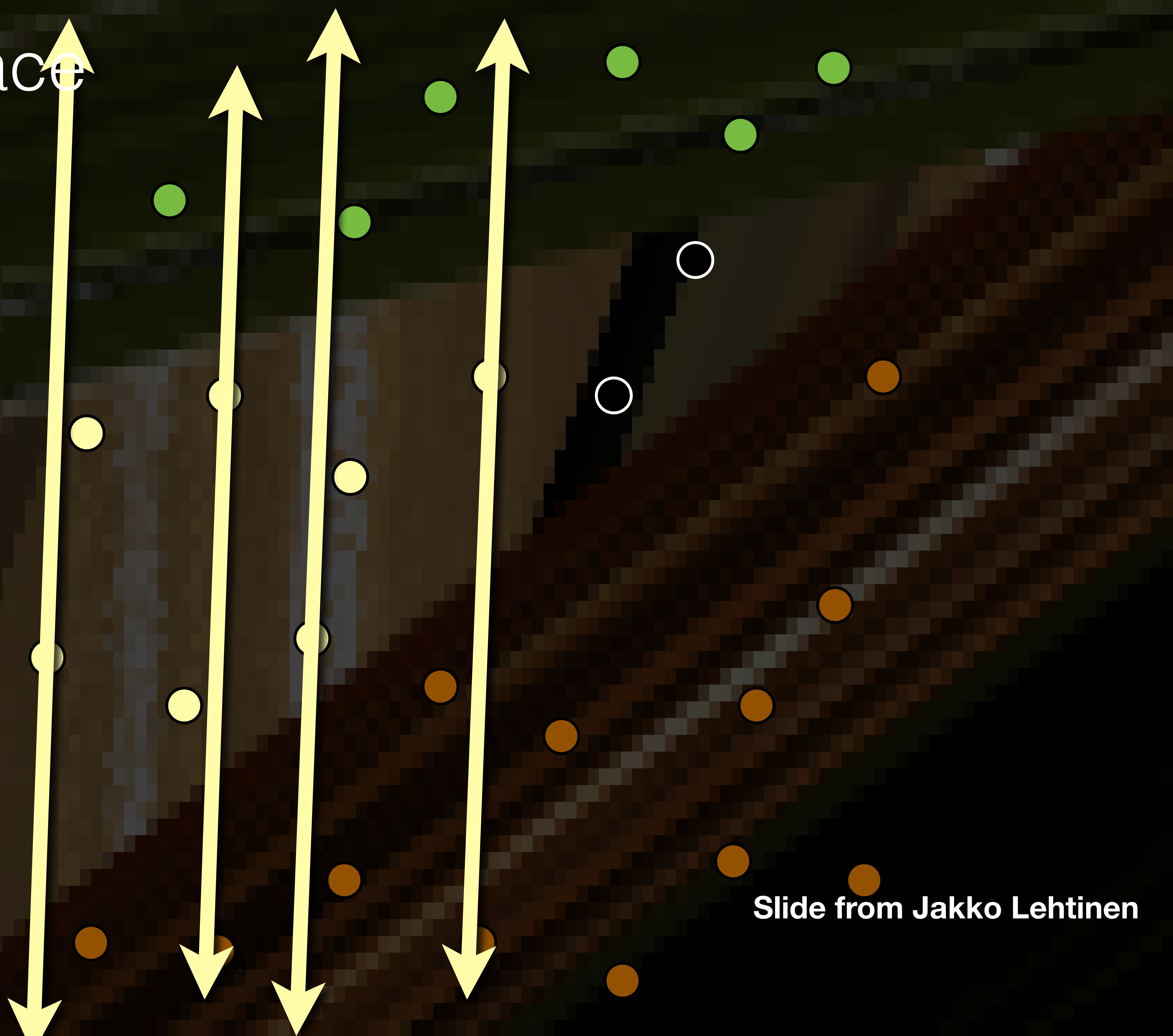
Visibility: SameSurface



The trajectories of samples originating from a single **apparent surface** never intersect.

Slide from Jakko Lehtinen

Visibility: SameSurface



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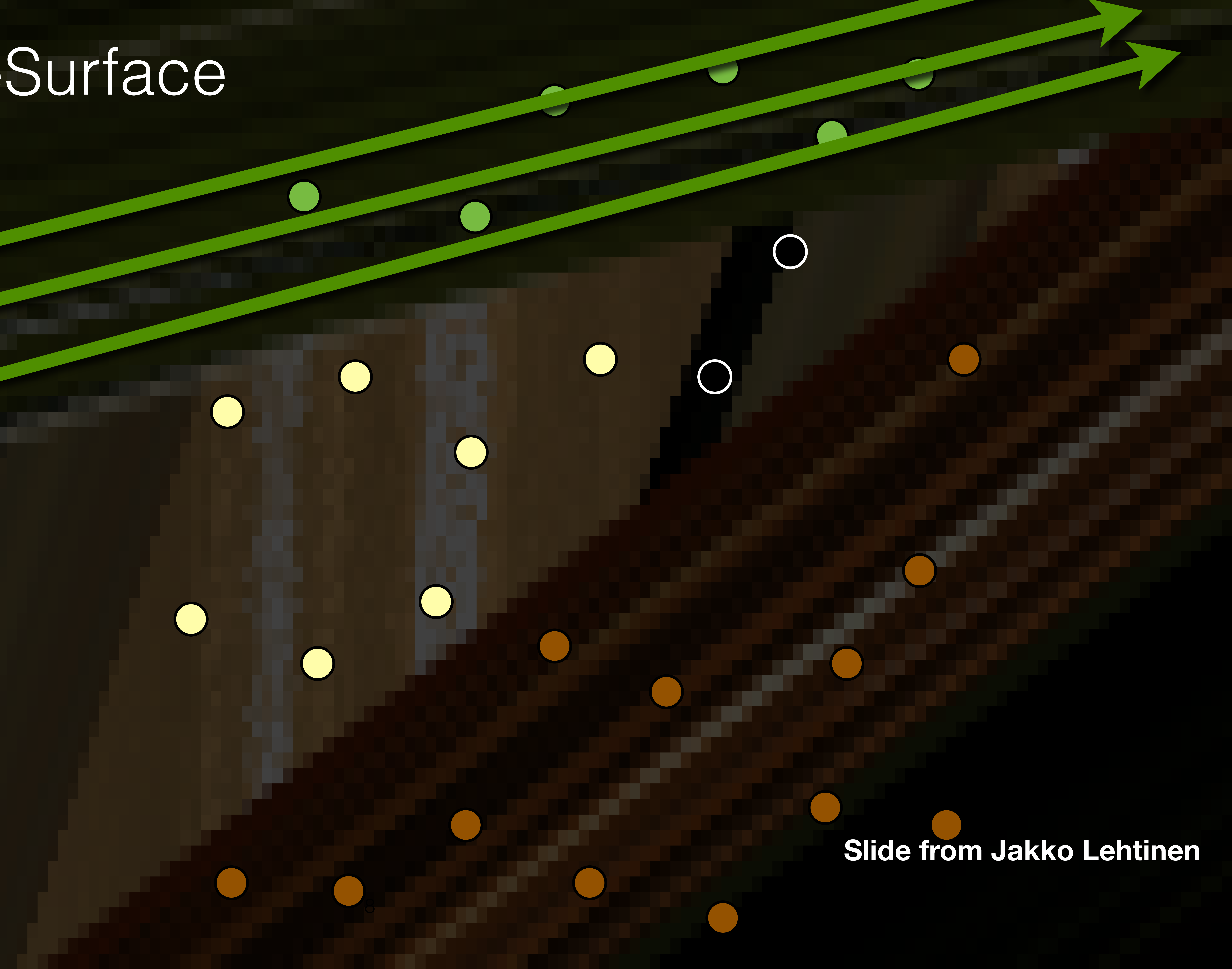

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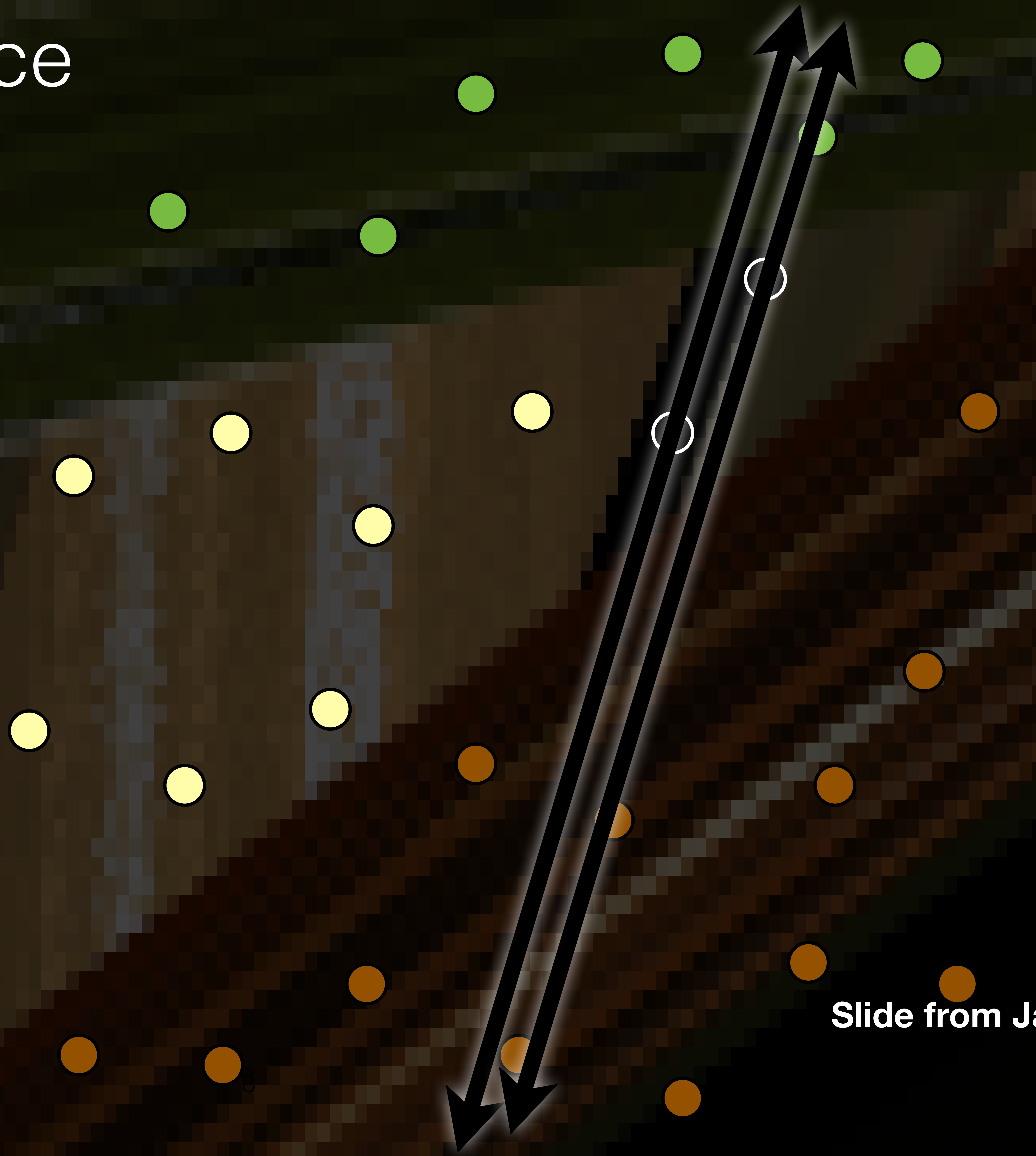
The trajectories of samples originating from a single **apparent surface** never intersect.



Slide from Jakko Lehtinen

Introduction
Denoising using Data

Path to Machine Learning

Introduction
Denoising using Data

Path to Machine Learning

MLP based Denoising

Introduction
Denoising using Data

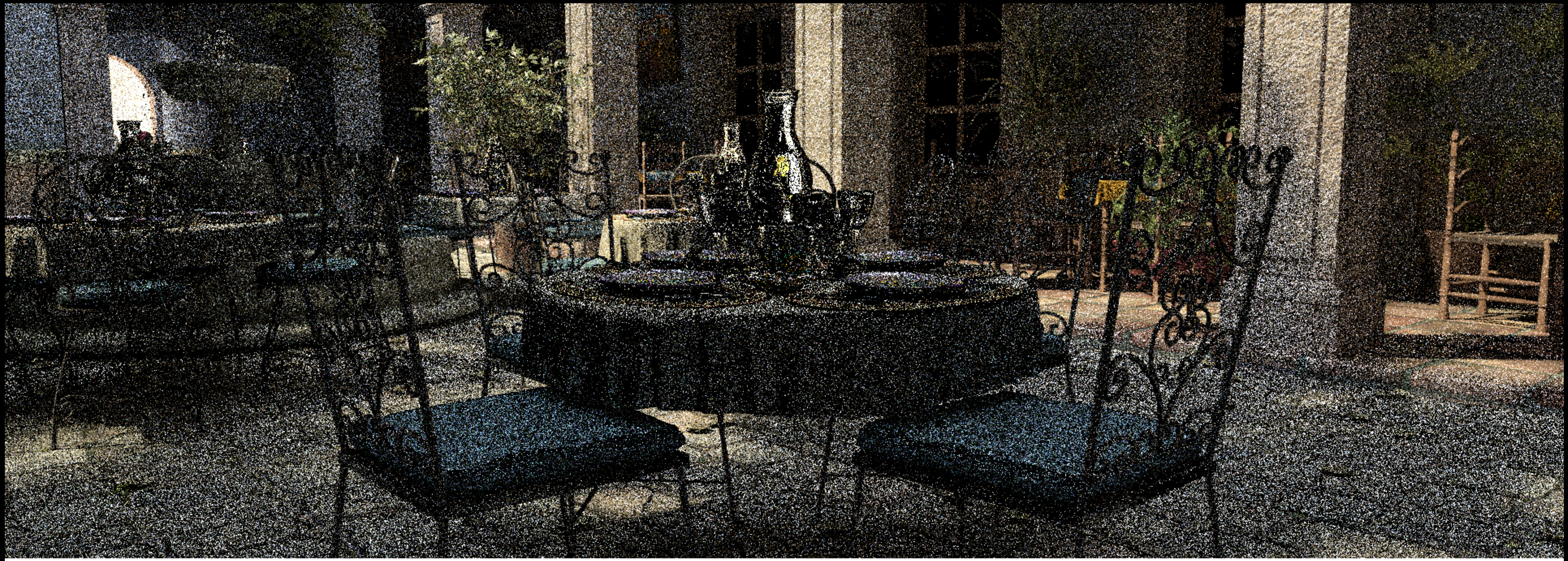
Path to Machine Learning

MLP based Denoising

CNN based Denosing
(Next lecture)

Filtering Monte Carlo Noise From Random Parameters

Sen and Darabi [2012]


input Monte Carlo (8 samples/pixel)


after RPF (8 samples/pixel)

High-dimensional Monte Carlo Integration

$$I(i,j) = \int_{i-\frac{1}{2}}^{i+\frac{1}{2}} \int_{j-\frac{1}{2}}^{j+\frac{1}{2}} \cdots \int_{-1}^{1} \int_{-1}^{1} \int_{t_0}^{t_1} f(x, y, \cdots, u, v, t)\, dt\, dv\, du \cdots dy\, dx$$

(a) Input MC (8 spp) **(b)** Dependency on (u, v) **(c)** Our approach (RPF)

Parameters in Monte Carlo estimator

Random parameters: $\mathbf{r} = \{r_1, r_2, \ldots, r_n\}$

Color: $\mathbf{c}_i \Leftarrow f(\underbrace{\mathbf{p}_{i,1}, \mathbf{p}_{i,2}}_{\text{screen position}}; \underbrace{\mathbf{r}_{i,1}, \mathbf{r}_{i,2}, \ldots, \mathbf{r}_{i,n}}_{\text{random parameters}})$

Random Parameters Classification

Random parameter for each pixel : $\mathbf{x}_i \Leftarrow f(\mathbf{p}_{i,1}, \mathbf{p}_{i,2}; \mathbf{r}_{i,1}, \mathbf{r}_{i,2}, \ldots, \mathbf{r}_{i,n})$

$$\mathbf{x}_i = \{\underbrace{\mathbf{p}_{i,1}, \mathbf{p}_{i,2}}_{\substack{\text{screen}\\\text{position}}}; \underbrace{\mathbf{r}_{i,1}, \ldots, \mathbf{r}_{i,n}}_{\substack{\text{random}\\\text{parameters}}}; \underbrace{\mathbf{f}_{i,1}, \ldots, \mathbf{f}_{i,m}}_{\substack{\text{scene}\\\text{features}}}; \underbrace{\mathbf{c}_{i,1}, \mathbf{c}_{i,2}, \mathbf{c}_{i,3}}_{\substack{\text{sample}\\\text{color}}}\}$$

Random Parameters Classification

Random parameter for each pixel :

$$\mathbf{x}_i \Leftarrow f(\mathbf{p}_{i,1}, \mathbf{p}_{i,2}; \mathbf{r}_{i,1}, \mathbf{r}_{i,2}, \ldots, \mathbf{r}_{i,n})$$

$$\mathbf{x}_i = \{\underbrace{\boxed{\mathbf{p}_{i,1}, \mathbf{p}_{i,2}}}_{\text{screen position}}; \underbrace{\mathbf{r}_{i,1}, \ldots, \mathbf{r}_{i,n}}_{\text{random parameters}}; \underbrace{\mathbf{f}_{i,1}, \ldots, \mathbf{f}_{i,m}}_{\text{scene features}}; \underbrace{\mathbf{c}_{i,1}, \mathbf{c}_{i,2}, \mathbf{c}_{i,3}}_{\text{sample color}}\}$$

Random Parameters Classification

Random parameter for each pixel :

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$$\mathbf{x}_i = \{\underbrace{\boxed{\mathbf{p}_{i,1}, \mathbf{p}_{i,2}}}_{\text{screen position}}; \underbrace{\boxed{\mathbf{r}_{i,1}, \ldots, \mathbf{r}_{i,n}}}_{\text{random parameters}}; \underbrace{\mathbf{f}_{i,1}, \ldots, \mathbf{f}_{i,m}}_{\text{scene features}}; \underbrace{\mathbf{c}_{i,1}, \mathbf{c}_{i,2}, \mathbf{c}_{i,3}}_{\text{sample color}}\}$$

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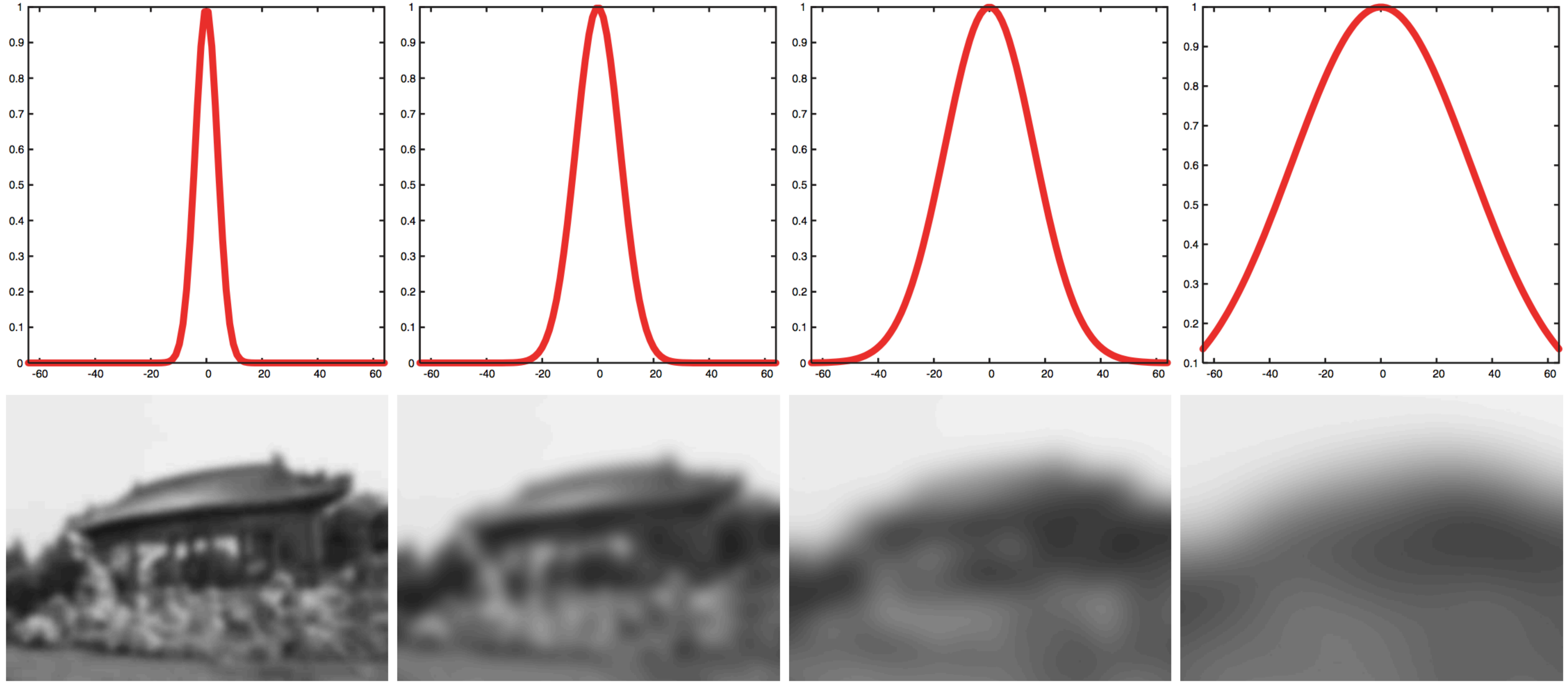
Gaussian Filtering



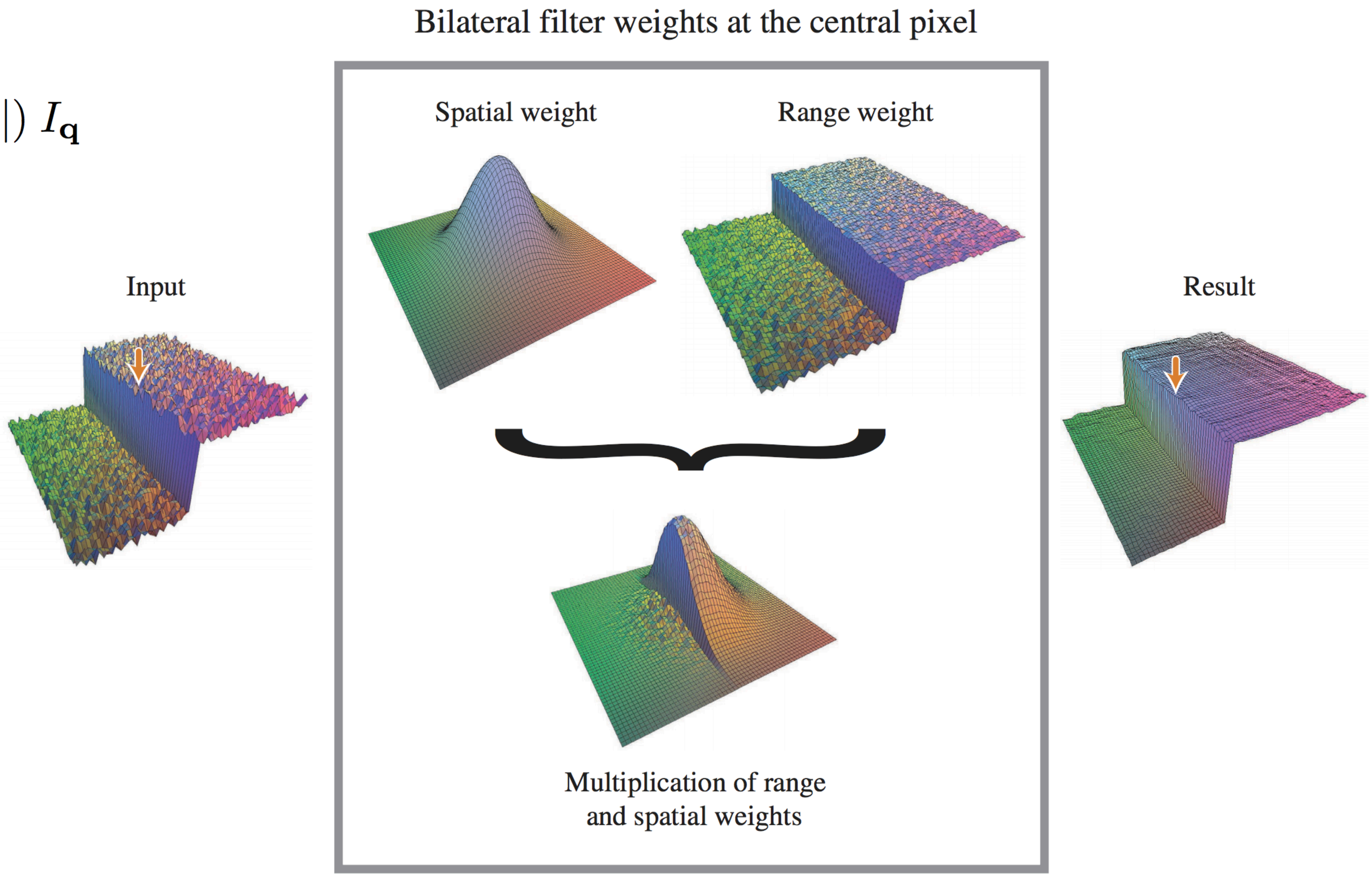
$\sigma = 4$ $\sigma = 8$ $\sigma = 16$ $\sigma = 32$

$$GC[I]_{\mathbf{p}} = \sum_{\mathbf{q} \in \mathcal{S}} G_\sigma(\|\mathbf{p} - \mathbf{q}\|)\, I_{\mathbf{q}}, \qquad G_\sigma(x) = \frac{1}{2\pi\,\sigma^2} \exp\left(-\frac{x^2}{2\,\sigma^2}\right)$$

Bilateral Filtering

$$BF[I]_{\mathbf{p}} = \frac{1}{W_{\mathbf{p}}} \sum_{\mathbf{q} \in \mathcal{S}} G_{\sigma_{\mathrm{s}}}(\|\mathbf{p} - \mathbf{q}\|)\, G_{\sigma_{\mathrm{r}}}(|I_{\mathbf{p}} - I_{\mathbf{q}}|)\, I_{\mathbf{q}}$$

$$W_{\mathbf{p}} = \sum_{\mathbf{q} \in \mathcal{S}} G_{\sigma_{\mathrm{s}}}(\|\mathbf{p} - \mathbf{q}\|)\, G_{\sigma_{\mathrm{r}}}(|I_{\mathbf{p}} - I_{\mathbf{q}}|)$$



Bilateral Filtering

$$BF[I]_{\mathbf{p}} = \frac{1}{W_{\mathbf{p}}} \sum_{\mathbf{q} \in \mathcal{S}} G_{\sigma_{\mathrm{s}}}(\|\mathbf{p} - \mathbf{q}\|) \boxed{G_{\sigma_{\mathrm{r}}}(|I_{\mathbf{p}} - I_{\mathbf{q}}|)} I_{\mathbf{q}}$$

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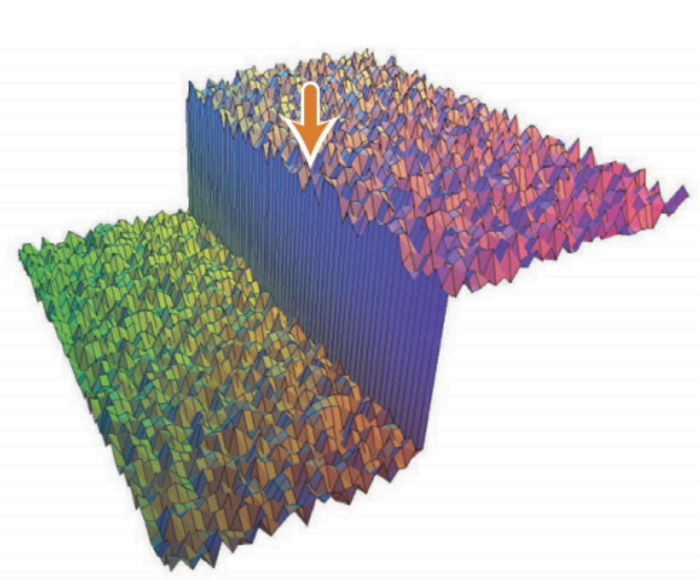
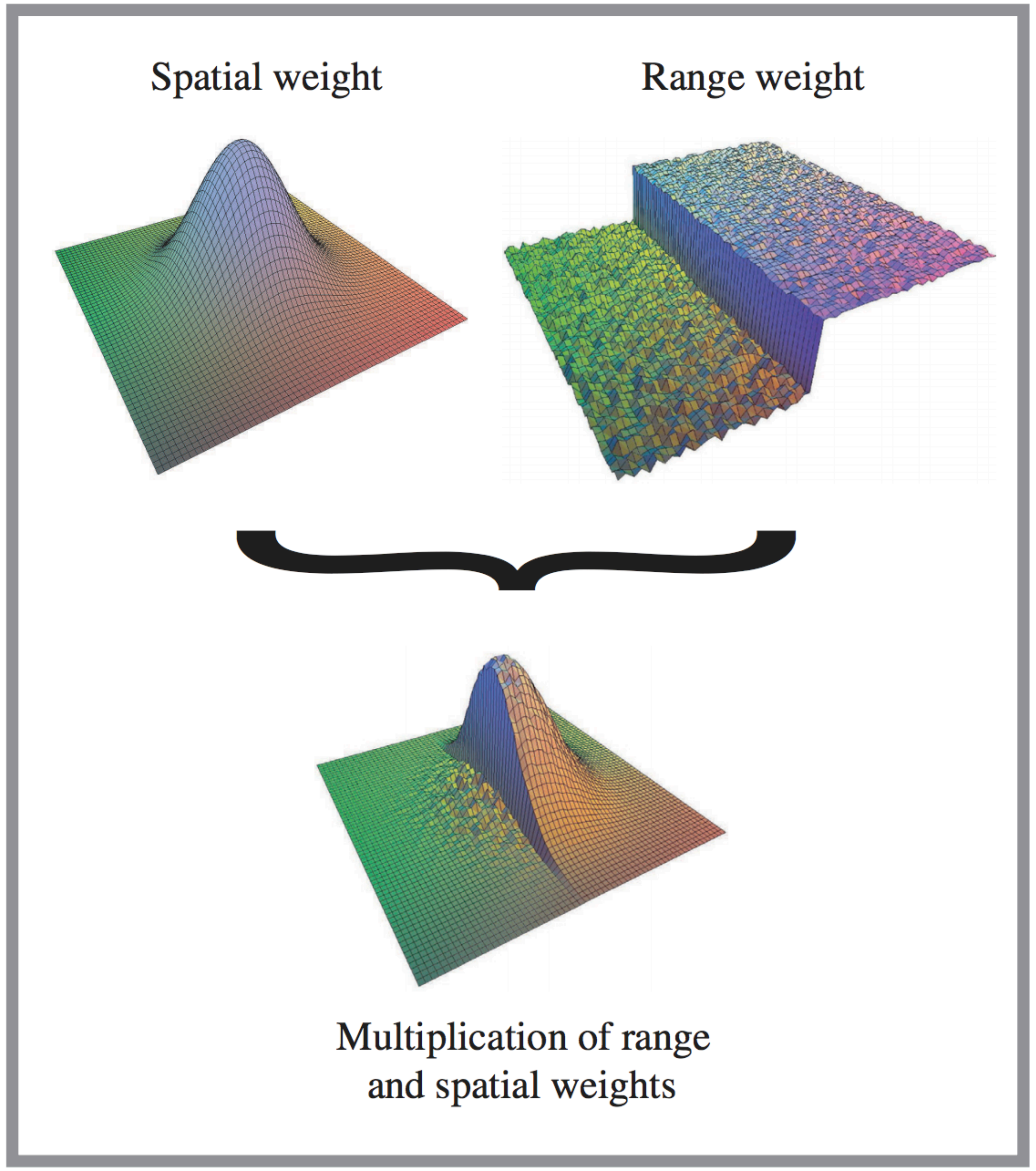
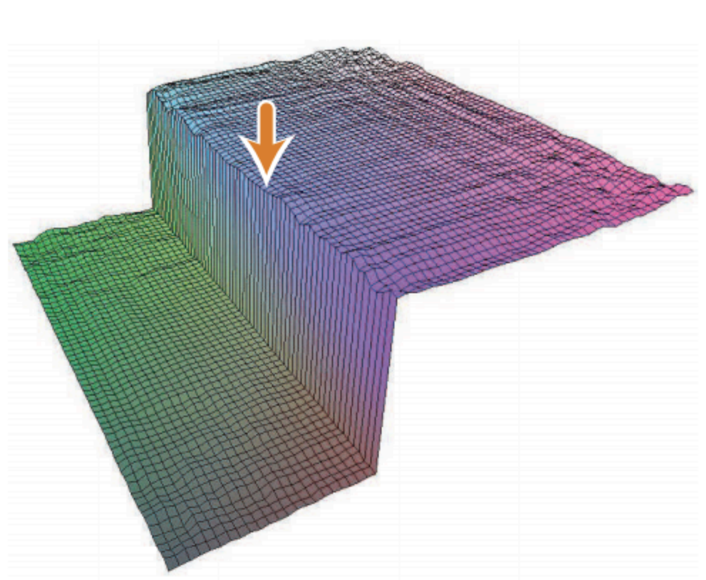
Input



Bilateral filter weights at the central pixel



Result



Bilateral Filtering

$$BF[I]_{\mathbf{p}} = \frac{1}{W_{\mathbf{p}}} \sum_{\mathbf{q} \in \mathcal{S}} G_{\sigma_s}(\|\mathbf{p} - \mathbf{q}\|) \boxed{G_{\sigma_r}(|I_{\mathbf{p}} - I_{\mathbf{q}}|)} I_{\mathbf{q}}$$

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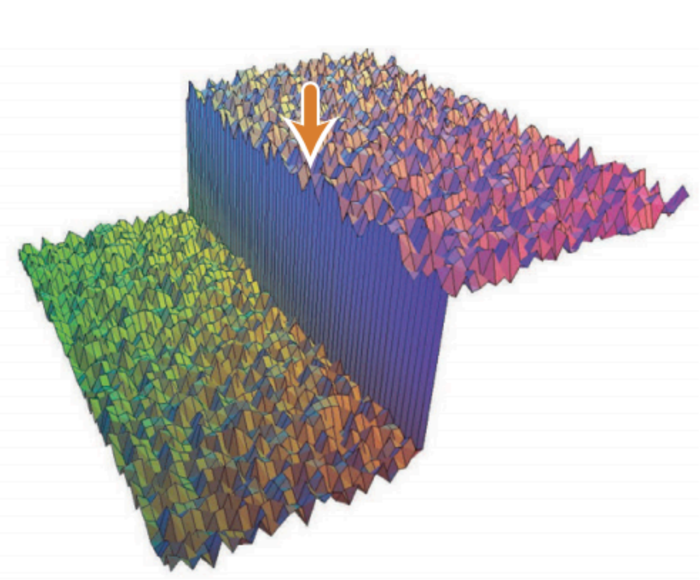

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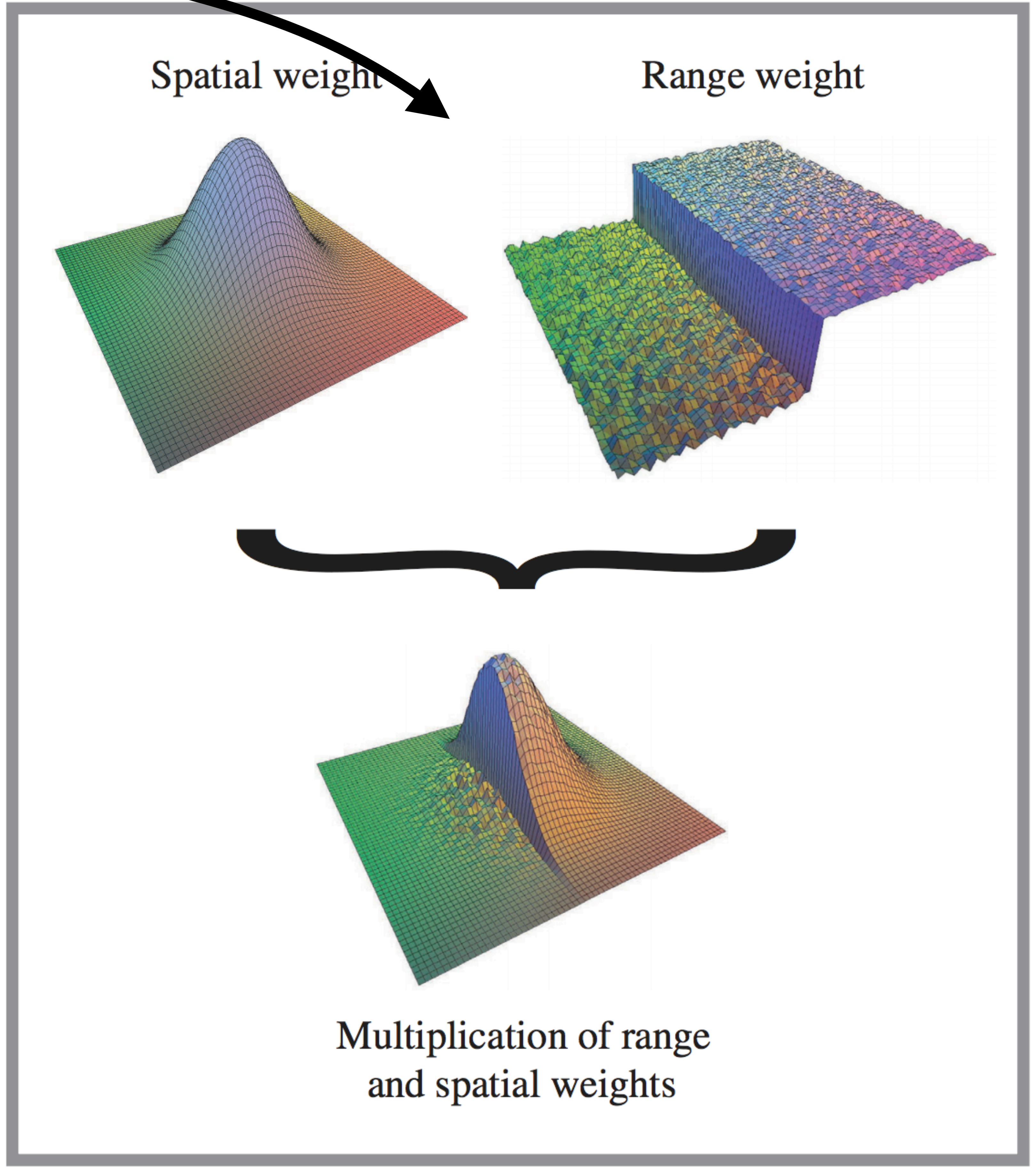

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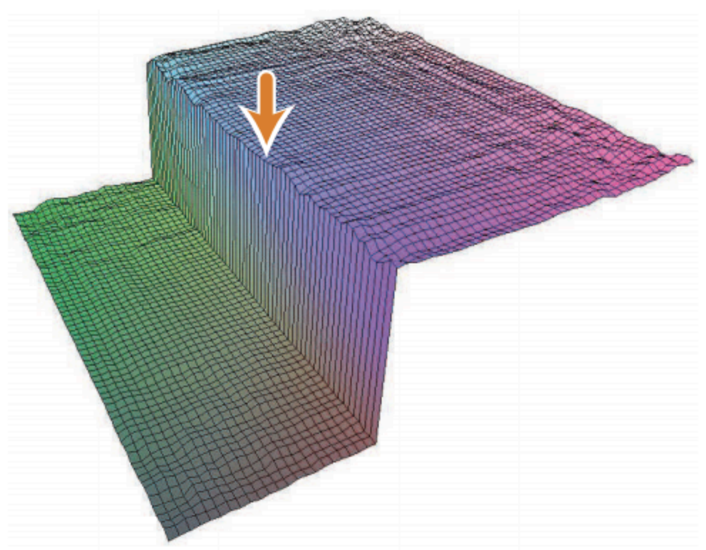

Bilateral Filtering

$$BF[I]_{\mathbf{p}} = \frac{1}{W_{\mathbf{p}}} \sum_{\mathbf{q} \in \mathcal{S}} \boxed{G_{\sigma_{\mathrm{s}}}(\|\mathbf{p} - \mathbf{q}\|)} \, \boxed{G_{\sigma_{\mathrm{r}}}(|I_{\mathbf{p}} - I_{\mathbf{q}}|)} \, I_{\mathbf{q}}$$

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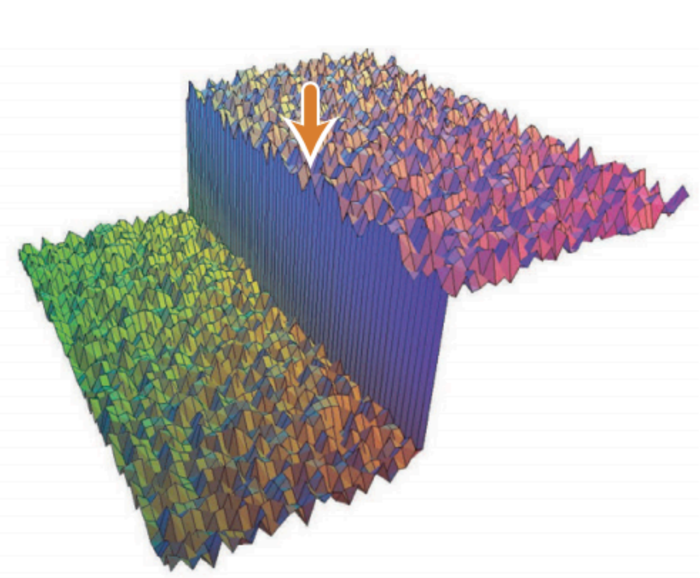
Input



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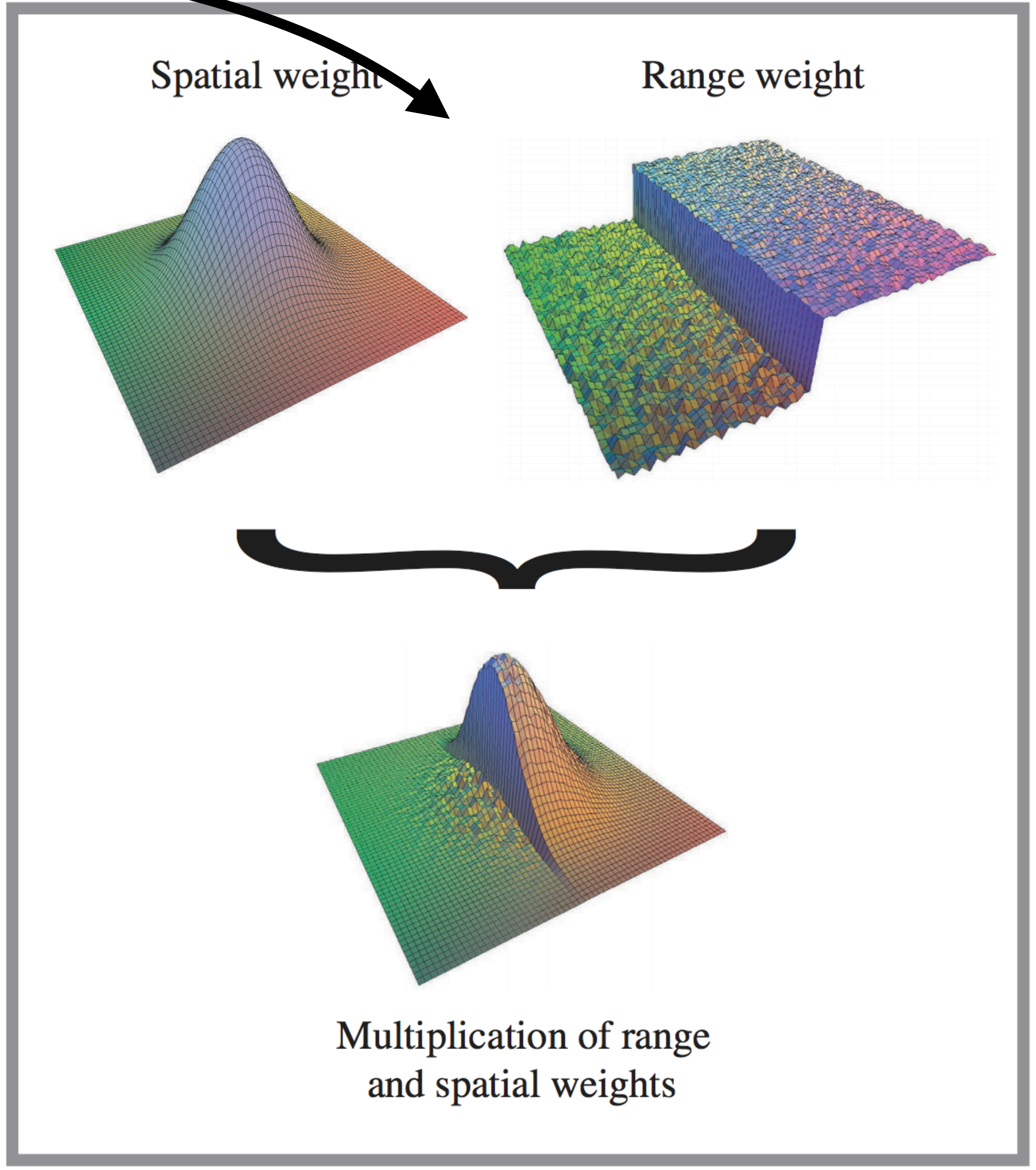
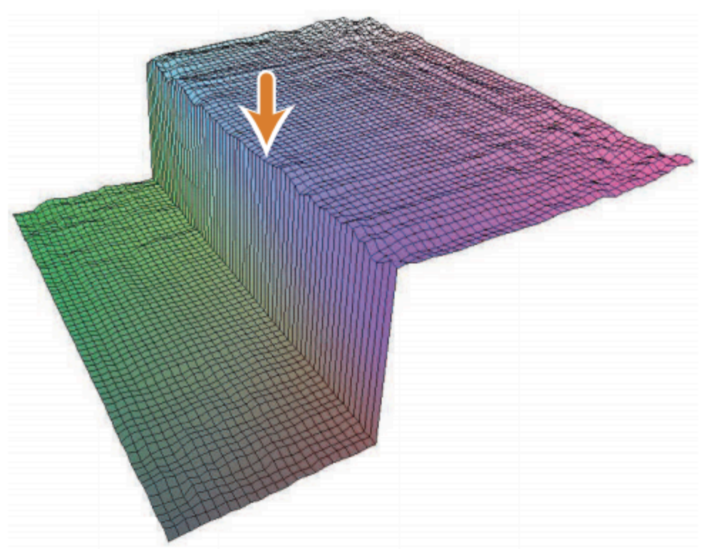


Result



Bilateral Filtering

$$BF[I]_{\mathbf{p}} = \frac{1}{W_{\mathbf{p}}} \sum_{\mathbf{q}\in\mathcal{S}} \boxed{G_{\sigma_{\mathrm{s}}}(\|\mathbf{p}-\mathbf{q}\|)}\, \boxed{G_{\sigma_{\mathrm{r}}}(|I_{\mathbf{p}}-I_{\mathbf{q}}|)}\, I_{\mathbf{q}}$$

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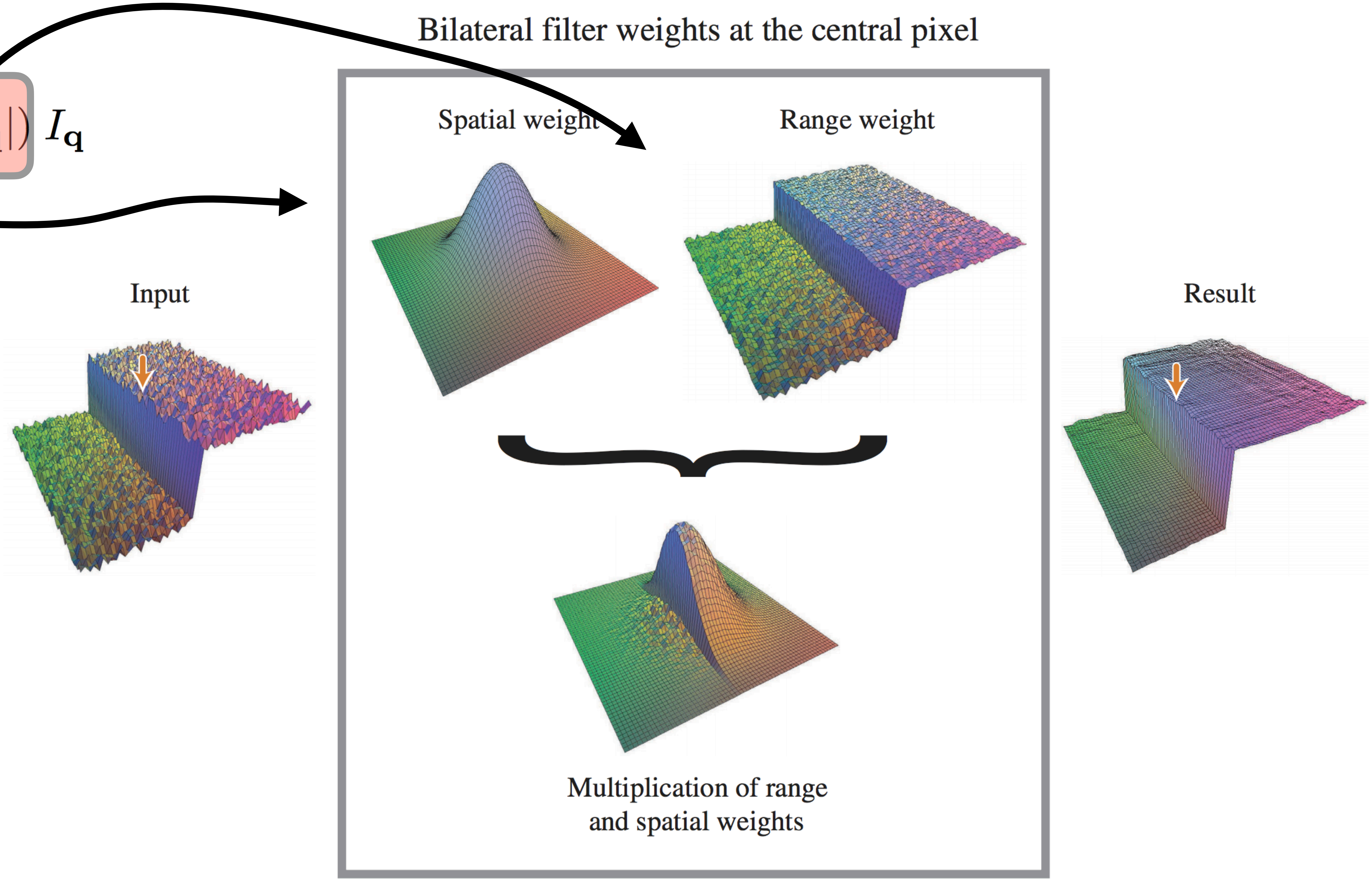

Bilateral Filtering

$$BF[I]_{\mathbf{p}} = \frac{1}{\boxed{W_{\mathbf{p}}}} \sum_{\mathbf{q} \in \mathcal{S}} \boxed{G_{\sigma_s}(\|\mathbf{p} - \mathbf{q}\|)}\ \boxed{G_{\sigma_r}(|I_{\mathbf{p}} - I_{\mathbf{q}}|)}\ I_{\mathbf{q}}$$

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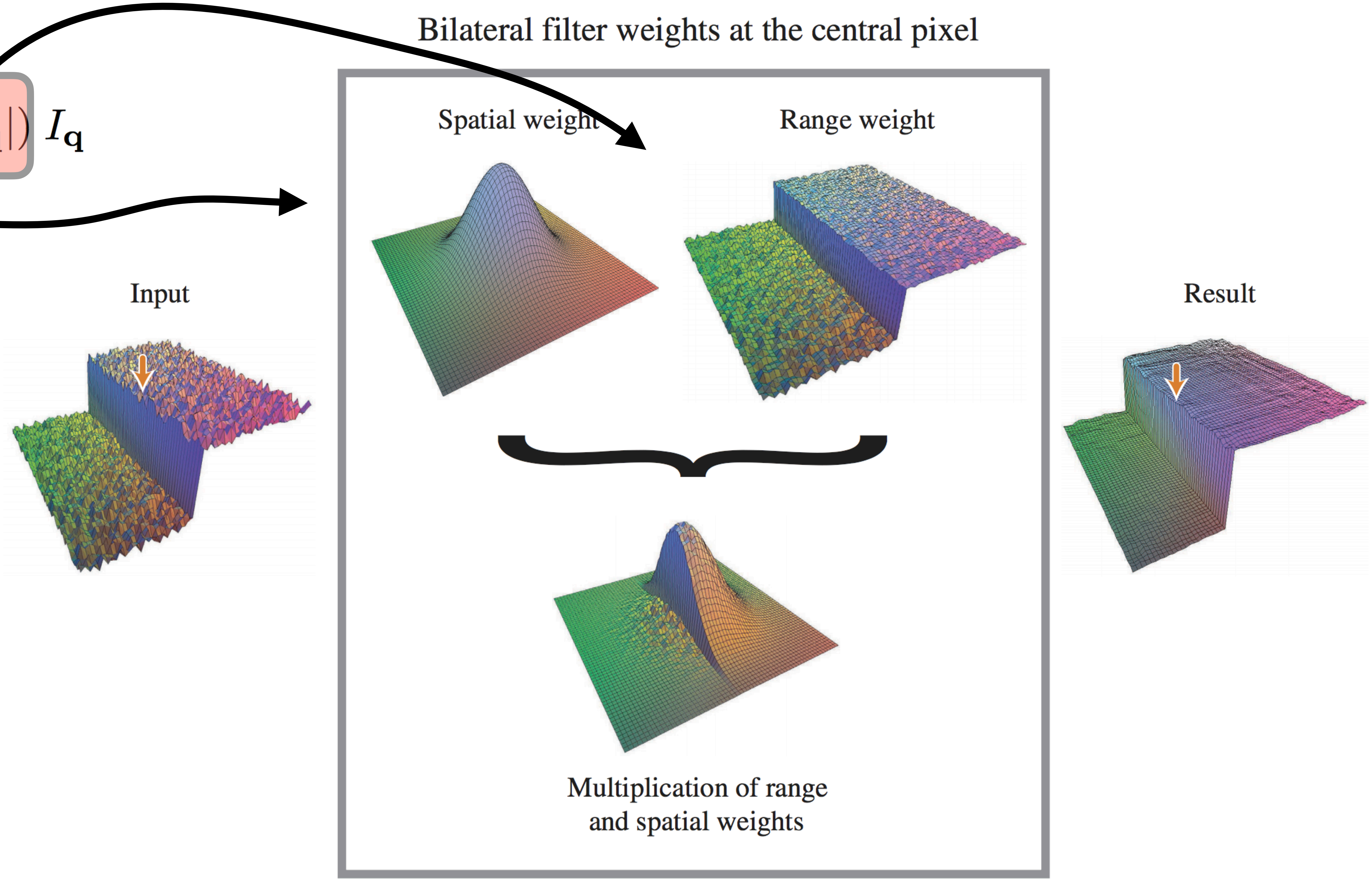

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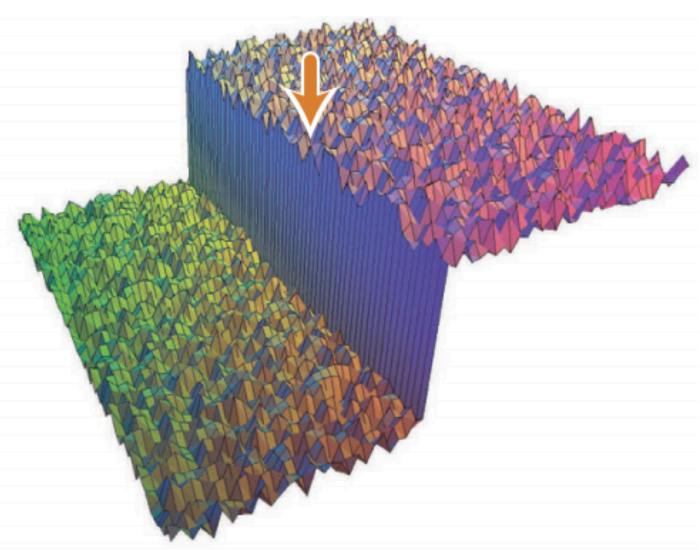
Input



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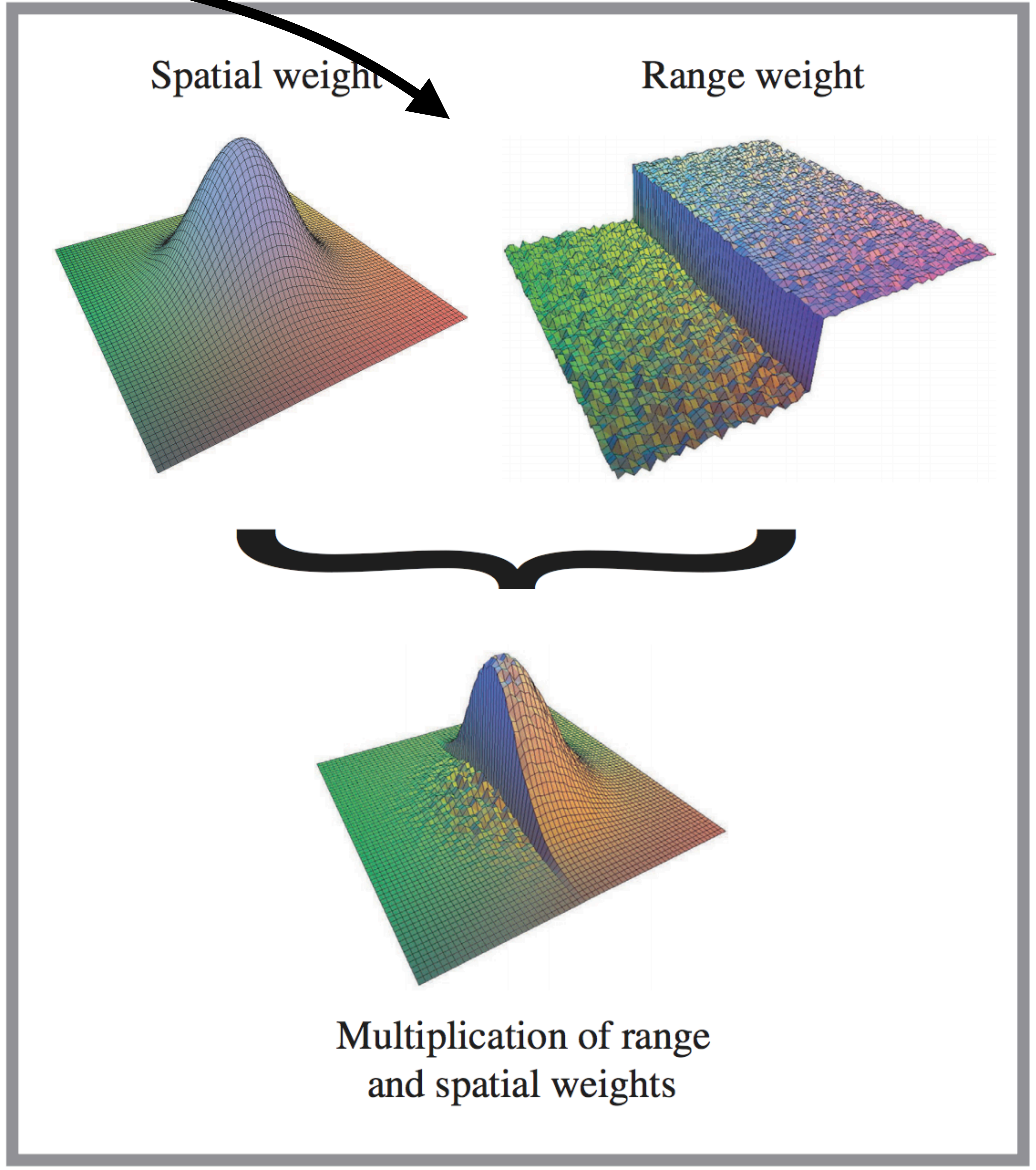
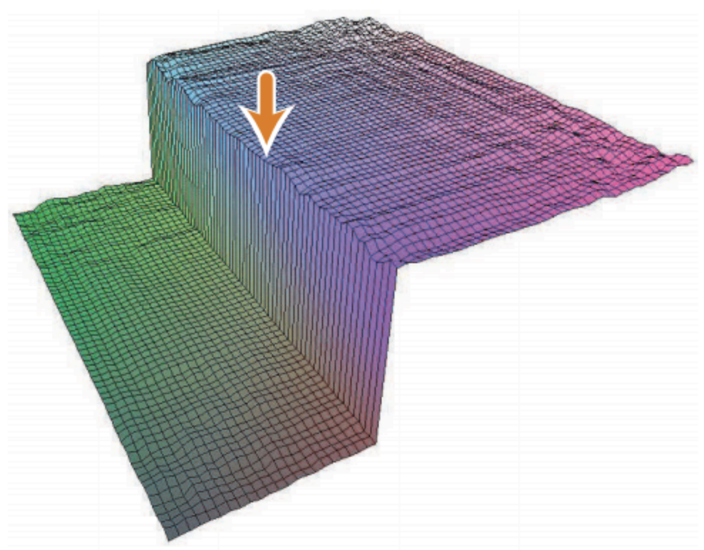
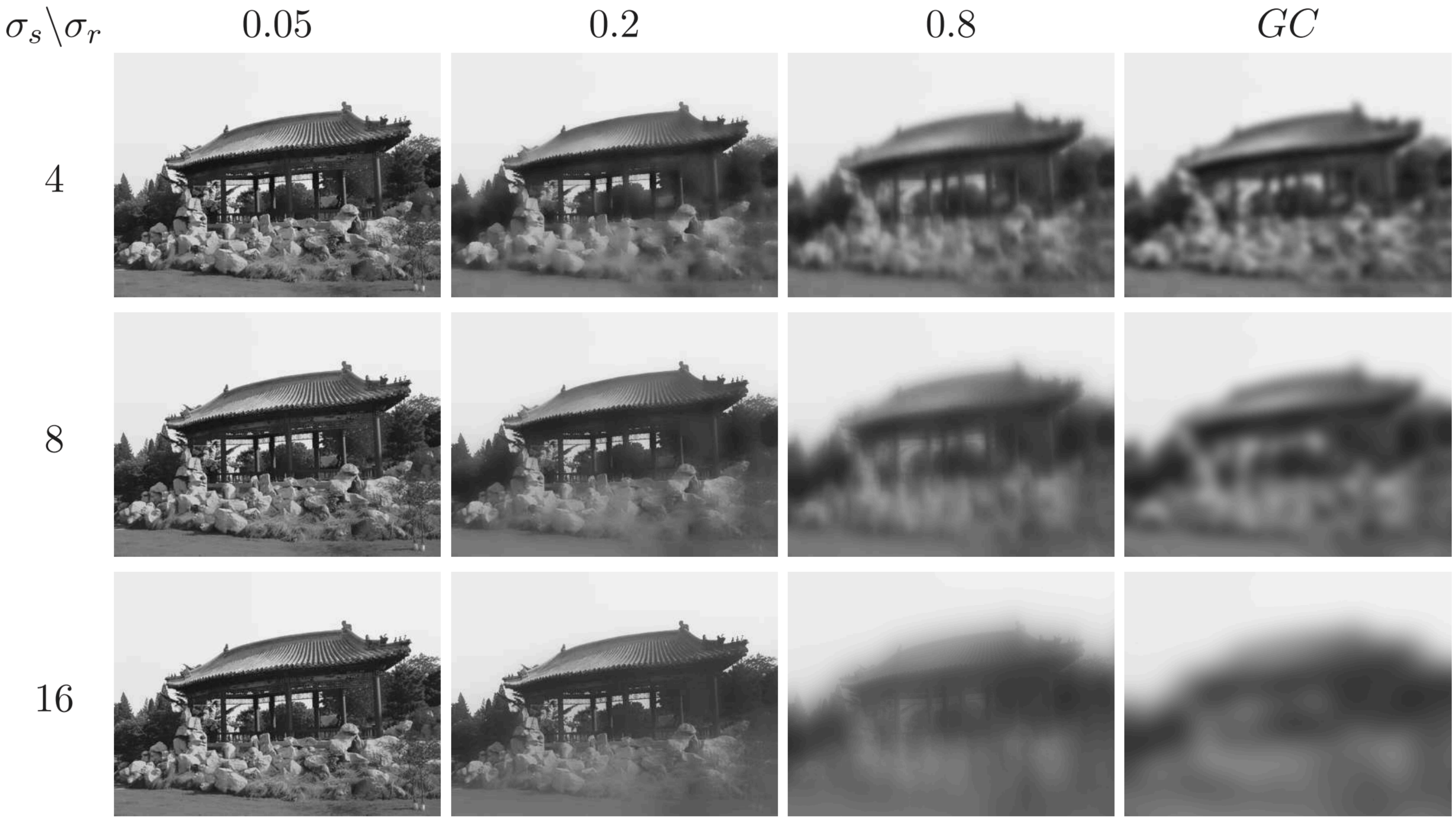


Result



Bilateral vs Gaussian Filtering



Bilateral Filtering of Features

$$w_{ij} = \exp[-\frac{1}{2\sigma_{\mathbf{p}}^2} \sum_{1 \le k \le 2} (\bar{\mathbf{p}}_{i,k} - \bar{\mathbf{p}}_{j,k})^2] \times$$

$$\exp[-\frac{1}{2\sigma_{\mathbf{c}}^2} \sum_{1 \le k \le 3} \boxed{\alpha_k} (\bar{\mathbf{c}}_{i,k} - \bar{\mathbf{c}}_{j,k})^2] \times$$

$$\exp[-\frac{1}{2\sigma_{\mathbf{f}}^2} \sum_{1 \le k \le m} \boxed{\beta_k} (\bar{\mathbf{f}}_{i,k} - \bar{\mathbf{f}}_{j,k})^2],$$

Dependency on Random Parameters

Input Monte Carlo (8 spp) | Dependency of color on random parameters ($D_{\mathbf{c}}^{\mathbf{r}}$) | Dependency of color on screen position ($D_{\mathbf{c}}^{\mathbf{p}}$) | Fractional dependency on random parameters ($W_{\mathbf{c}}^{\mathbf{r}}$) | Our approach (RPF) | Reference MC (512 spp)

Bilateral Weights

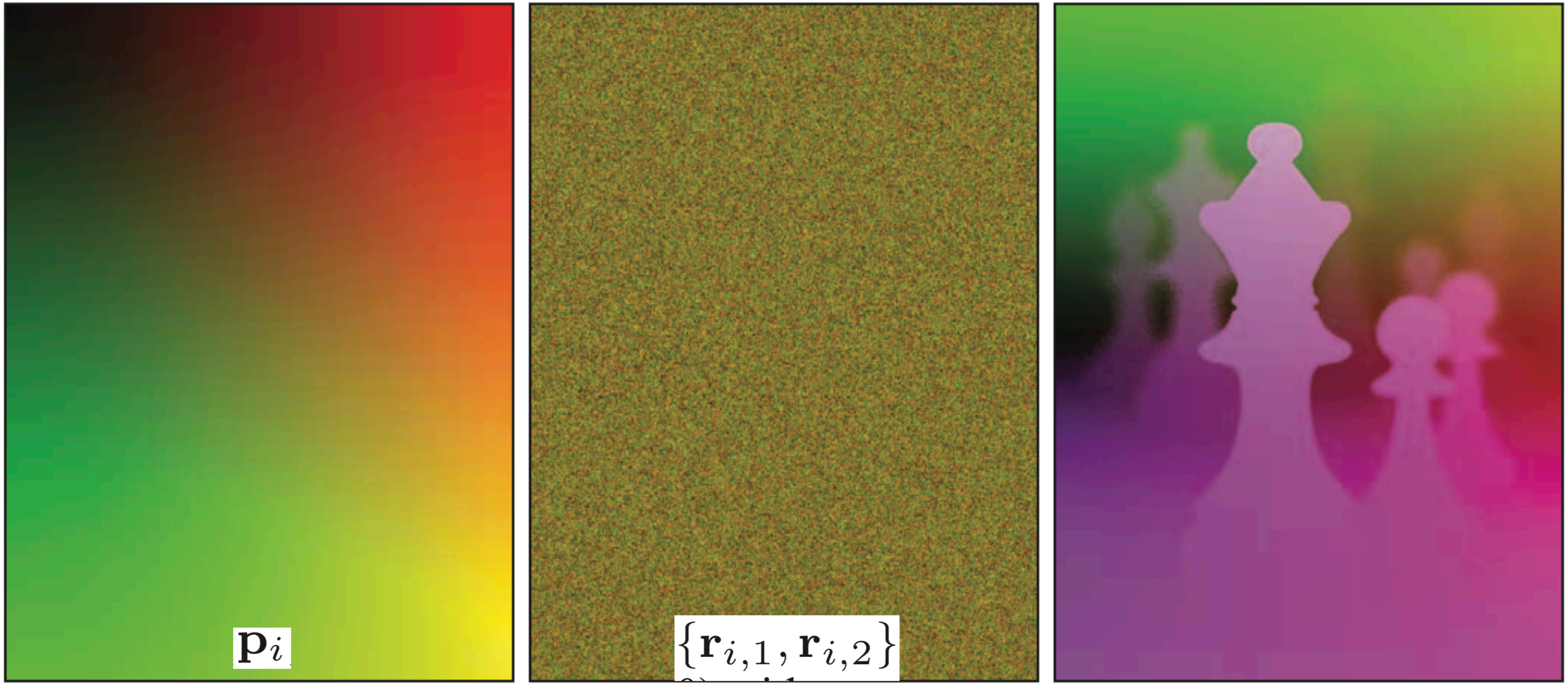
$$W^{\mathbf{r}}_{\mathbf{f},k} = \frac{D^{\mathbf{r}}_{\mathbf{f},k}}{D^{\mathbf{r}}_{\mathbf{f},k} + D^{\mathbf{p}}_{\mathbf{f},k}}$$

$$\boxed{\beta_k} = 1 - W^{\mathbf{r}}_{\mathbf{f},k}$$

$$W^{\mathbf{r}}_{\mathbf{c},k} = \frac{D^{\mathbf{r}}_{\mathbf{c},k}}{D^{\mathbf{r}}_{\mathbf{c},k} + D^{\mathbf{p}}_{\mathbf{c},k}}$$

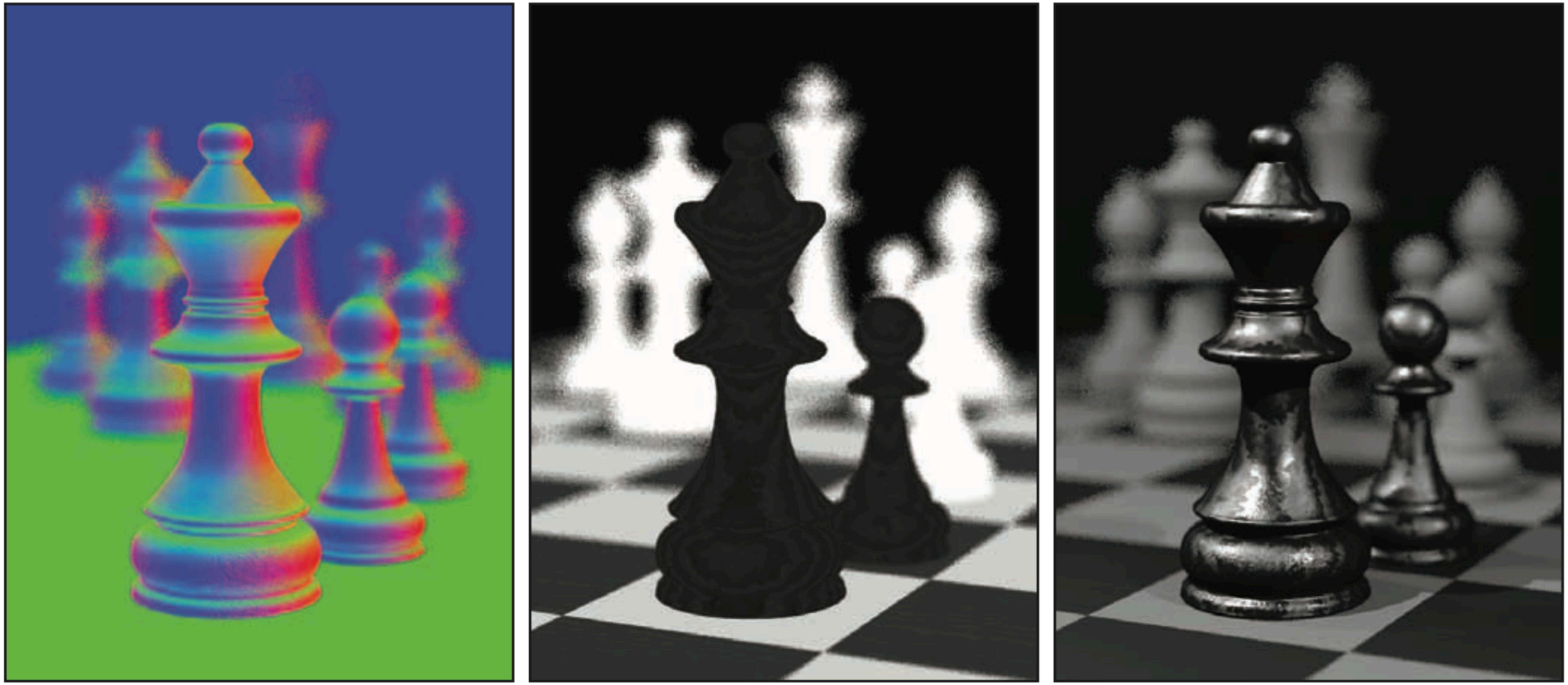
$$\boxed{\alpha_k} = 1 - W^{\mathbf{r}}_{\mathbf{c},k}.$$

Pixels,Random Params,Features



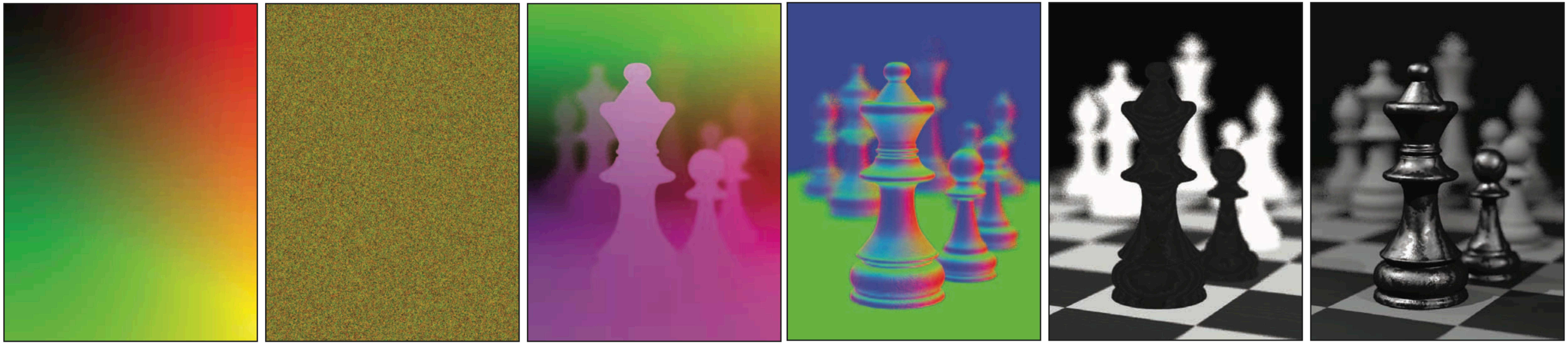
(a) Screen position **(b)** Random parameters **(c)** World space coords.

Pixels,Random Params,Features



(d) Surface normals (e) Texture value (f) Sample color

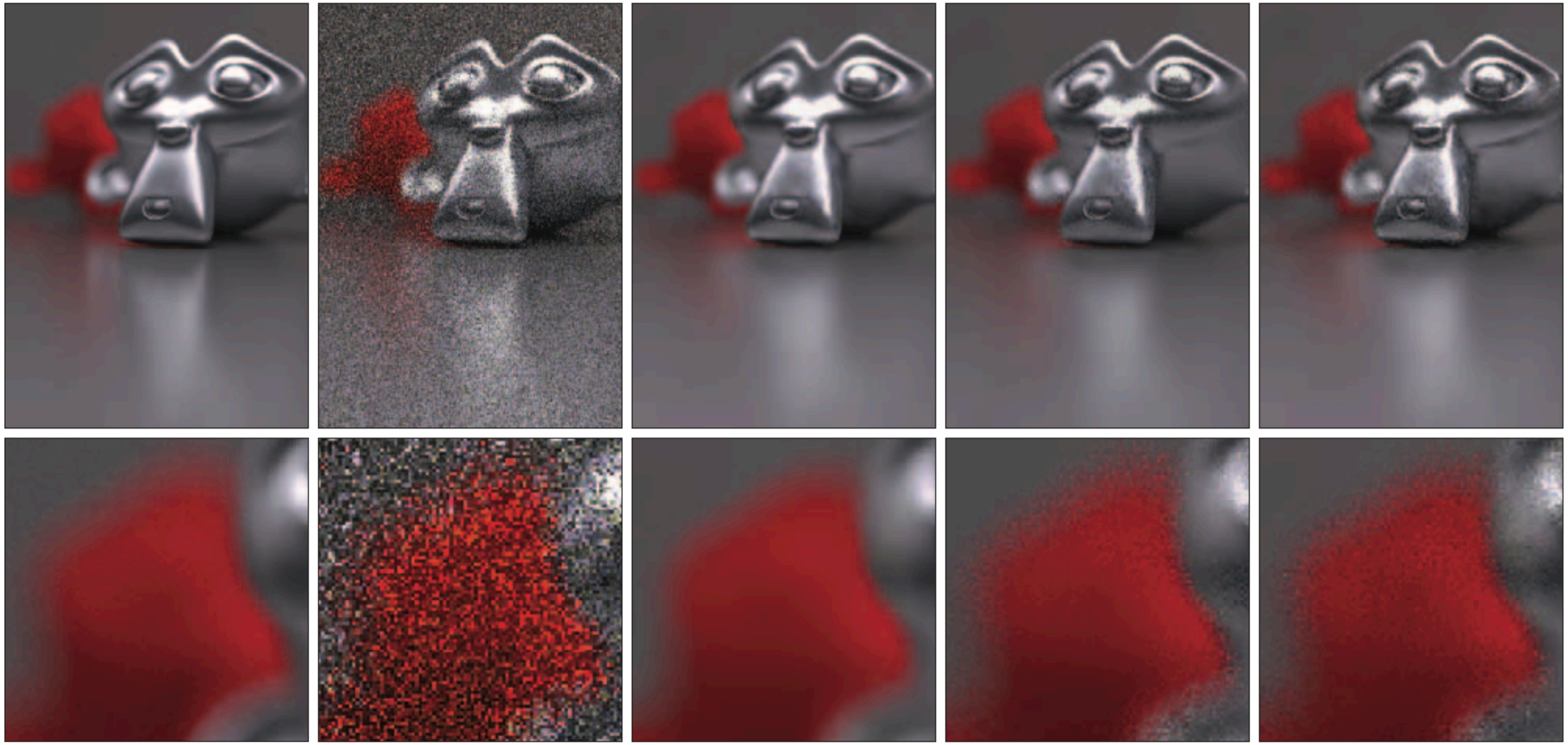
Pixels,Random Params,Features



(a) Screen position (b) Random parameters (c) World space coords. (d) Surface normals (e) Texture value (f) Sample color

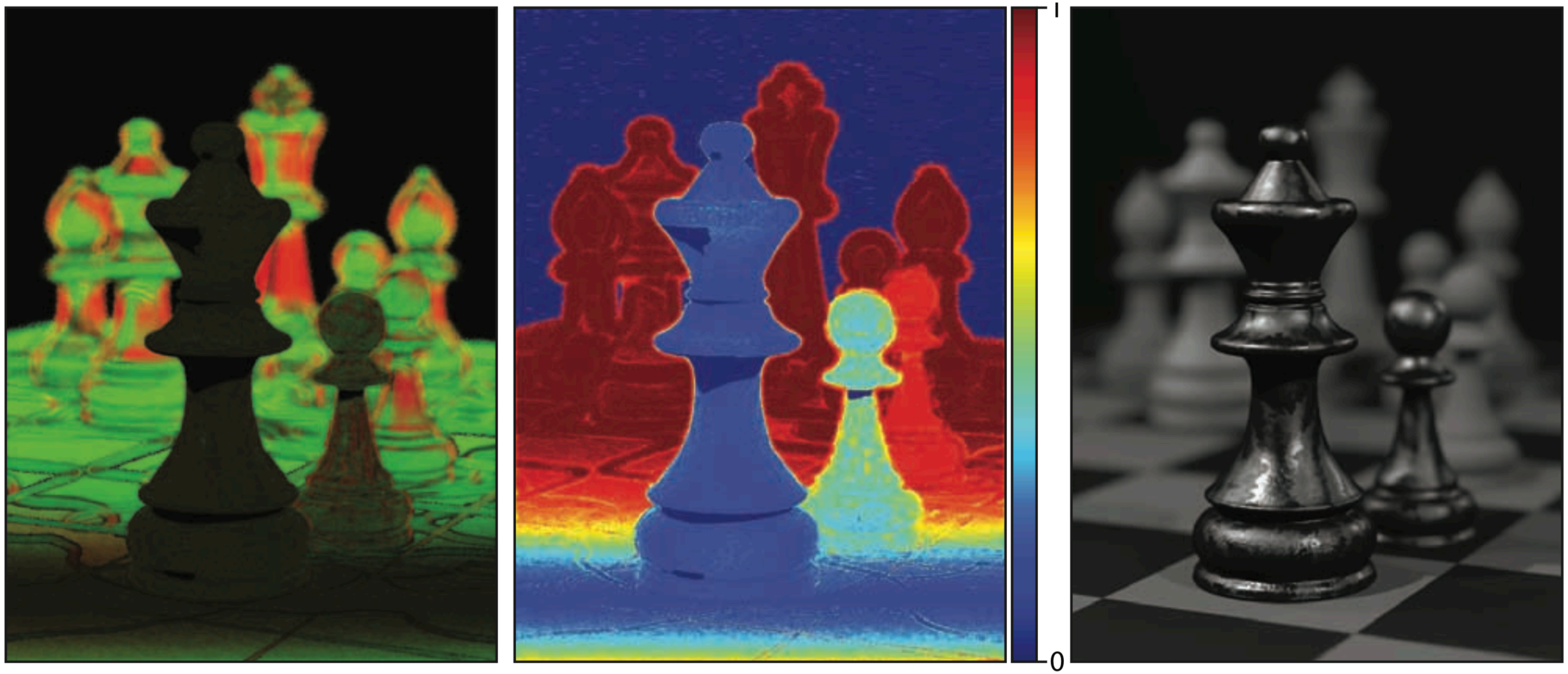
The algorithm computes the statistical dependency of **(c-f)** on the random parameters in (**b**)

Random Parameter Filtering



(a) Reference (b) MC Input (c) RPF (d) no clustering (e) no DoF params

Random Parameter Filtering



(a) $W^{\mathbf{r},1}_{\mathbf{c},k}$ and $W^{\mathbf{r},2}_{\mathbf{c},k}$ (b) $W^{\mathbf{r}}_{\mathbf{c},k}$ (c) Our output (RPF)

Statistical Dependency

Mutual information between two random variables:

$$\mu(X;Y) = \sum_{x\in X}\sum_{y\in Y} p(x,y)\log\frac{p(x,y)}{p(x)p(y)}$$

where, these probabilities are computed over
the neighborhood of samples around a given pixel

Statistical Dependency

Functional dependency of the k-th scene parameter:

$$D^{\mathbf{r}}_{\mathbf{f},k} = \sum_{1 \le l \le n} D^{\mathbf{r},l}_{\mathbf{f},k} = \sum_{1 \le l \le n} \mu(\bar{\mathbf{f}}_{\mathcal{N},k}; \bar{\mathbf{r}}_{\mathcal{N},l})$$

$$D^{\mathbf{p}}_{\mathbf{f},k} = \sum_{1 \le l \le 2} D^{\mathbf{p},l}_{\mathbf{f},k} = \sum_{1 \le l \le 2} \mu(\bar{\mathbf{f}}_{\mathcal{N},k}; \bar{\mathbf{p}}_{\mathcal{N},l}),$$

$$D^{\mathbf{r}}_{\mathbf{c},k} = \sum_{1 \le l \le n} D^{\mathbf{r},l}_{\mathbf{c},k} = \sum_{1 \le l \le n} \mu(\bar{\mathbf{c}}_{\mathcal{N},k}; \bar{\mathbf{r}}_{\mathcal{N},l}),$$

$$D^{\mathbf{p}}_{\mathbf{c},k} = \sum_{1 \le l \le 2} D^{\mathbf{p},l}_{\mathbf{c},k} = \sum_{1 \le l \le 2} \mu(\bar{\mathbf{c}}_{\mathcal{N},k}; \bar{\mathbf{p}}_{\mathcal{N},l}).$$

Statistical Dependency

$$D^{\mathbf{r}}_{\mathbf{f},k} = \sum_{1 \le l \le n} D^{\mathbf{r},l}_{\mathbf{f},k} = \sum_{1 \le l \le n} \mu(\bar{\mathbf{f}}_{\mathcal{N},k}; \bar{\mathbf{r}}_{\mathcal{N},l})$$

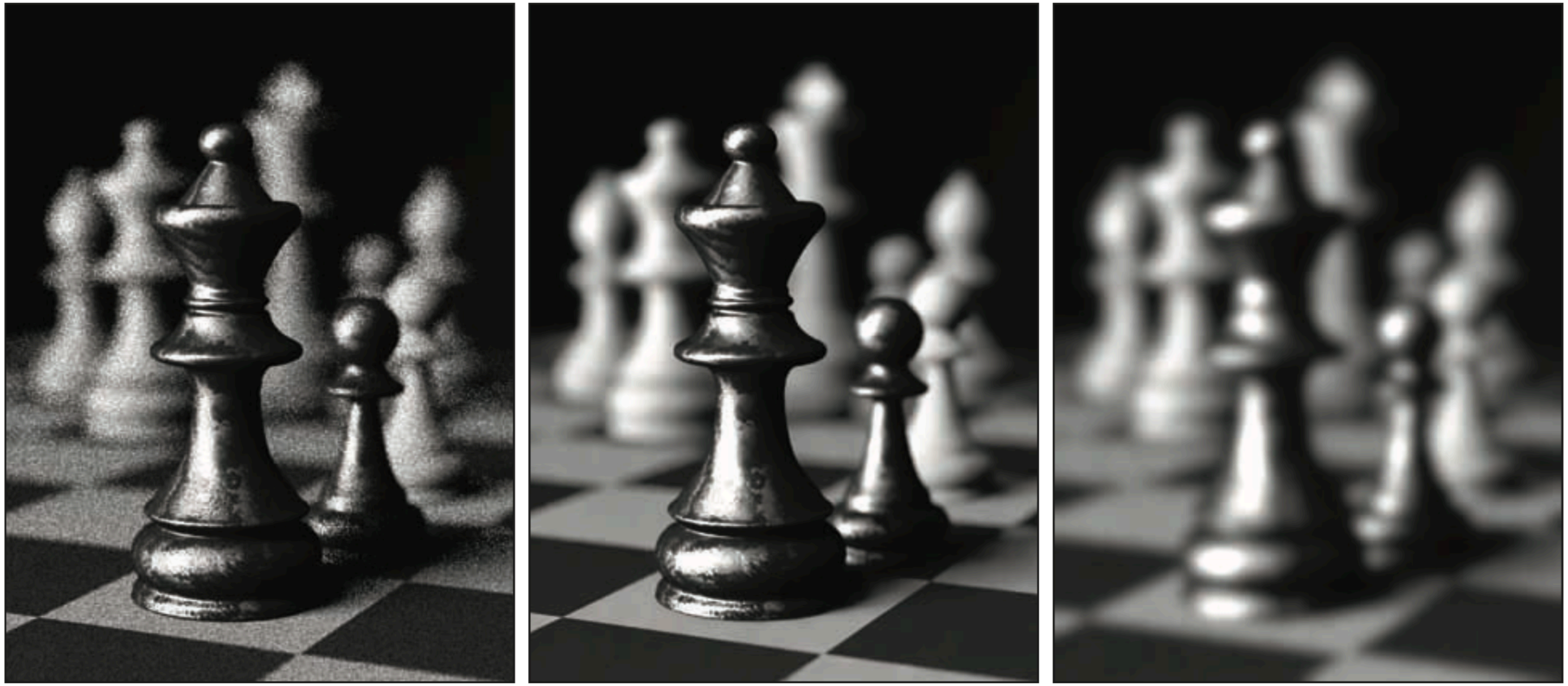
$$W^{\mathbf{f},k}_{\mathbf{c}} = \frac{D^{\mathbf{f},k}_{\mathbf{c}}}{D^{\mathbf{r}}_{\mathbf{c}} + D^{\mathbf{p}}_{\mathbf{c}} + D^{\mathbf{f}}_{\mathbf{c}}}$$

$$D^{\mathbf{r}}_{\mathbf{c}} = \sum_{1 \le k \le 3} D^{\mathbf{r}}_{\mathbf{c},k}, \quad D^{\mathbf{p}}_{\mathbf{c}} = \sum_{1 \le k \le 3} D^{\mathbf{p}}_{\mathbf{c},k}, \quad D^{\mathbf{f}}_{\mathbf{c}} = \sum_{1 \le k \le 3} D^{\mathbf{f}}_{\mathbf{c},k}$$

Weighted Average Bilateral Filtering

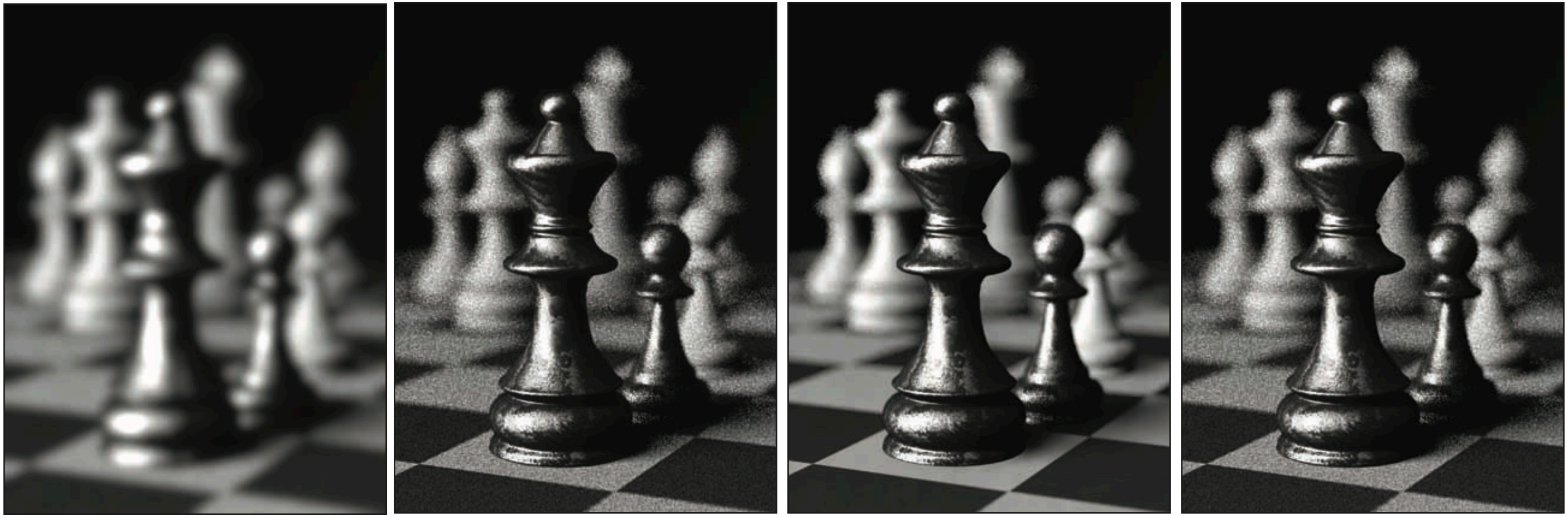
$$\mathbf{c}'_{i,k} = \frac{\sum_{j \in \mathcal{N}} w_{ij} \mathbf{c}_{j,k}}{\sum_{j \in \mathcal{N}} w_{ij}}$$

Results



(a) MC Input (8 spp) **(b)** Our approach (RPF) **(c)** $\alpha_k = 0$, $\beta_k = 0$

Results



) **(c)** $\alpha_k = 0, \beta_k = 0$ **(d)** $\alpha_k = 1, \beta_k = 0$ **(e)** $\alpha_k = 0, \beta_k = 1$ **(f)** $\alpha_k = 1, \beta_k = 1$

Results

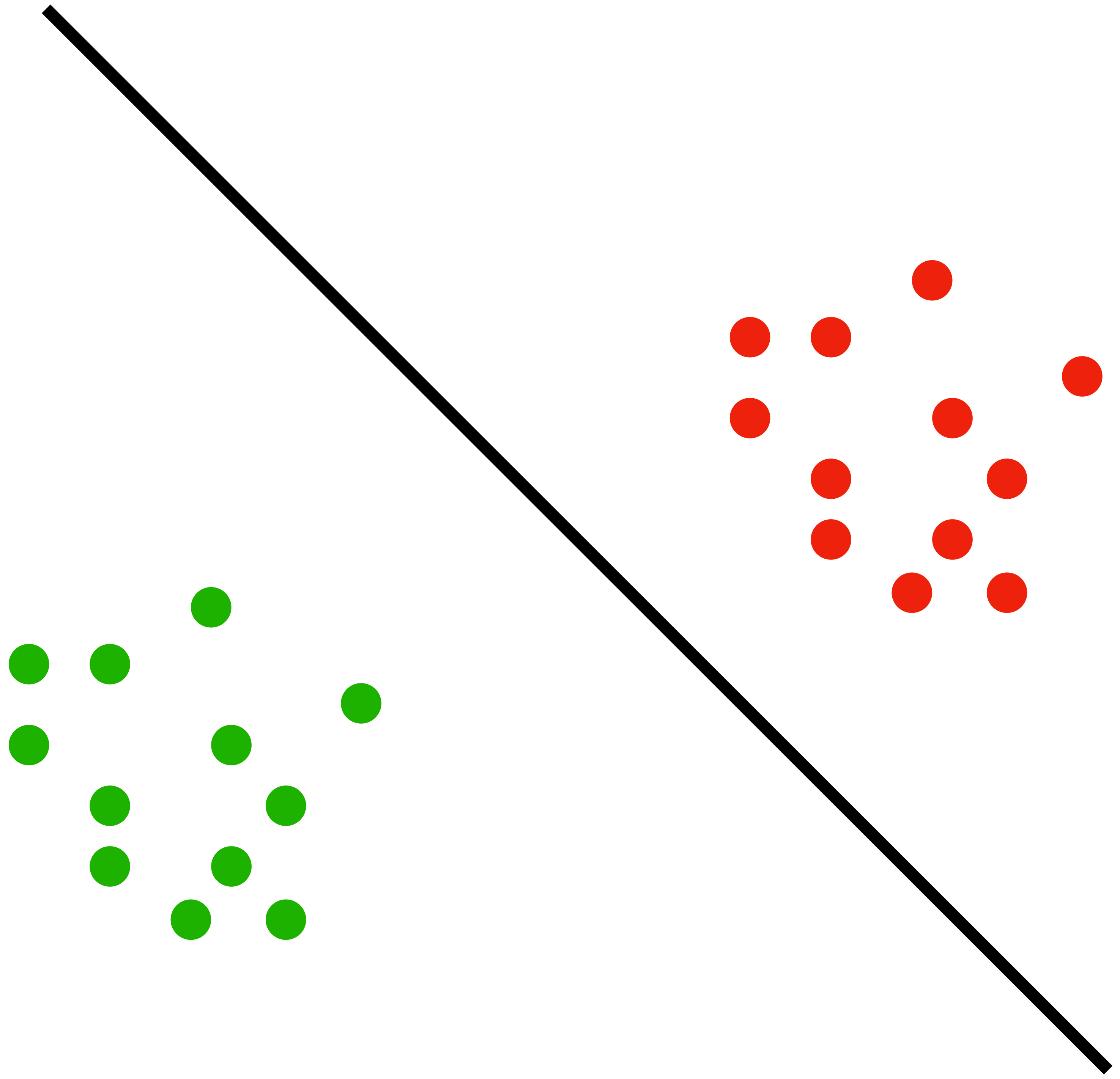

Reference (8,192 spp)
Input Monte Carlo (8 spp)
MDAS
AWR
À-Trous
Our approach (RPF)

Multi-Layer Perceptrons

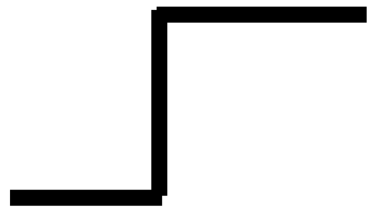
History of Neural Networks

- In 1943, McCulloch and Pitts created a computational model for neural networks
- In 1975, Werbos's back propagation algorithm generally accelerated the training of multi-layer networks.
- In 1980s, Recurrent Neural Networks were developed

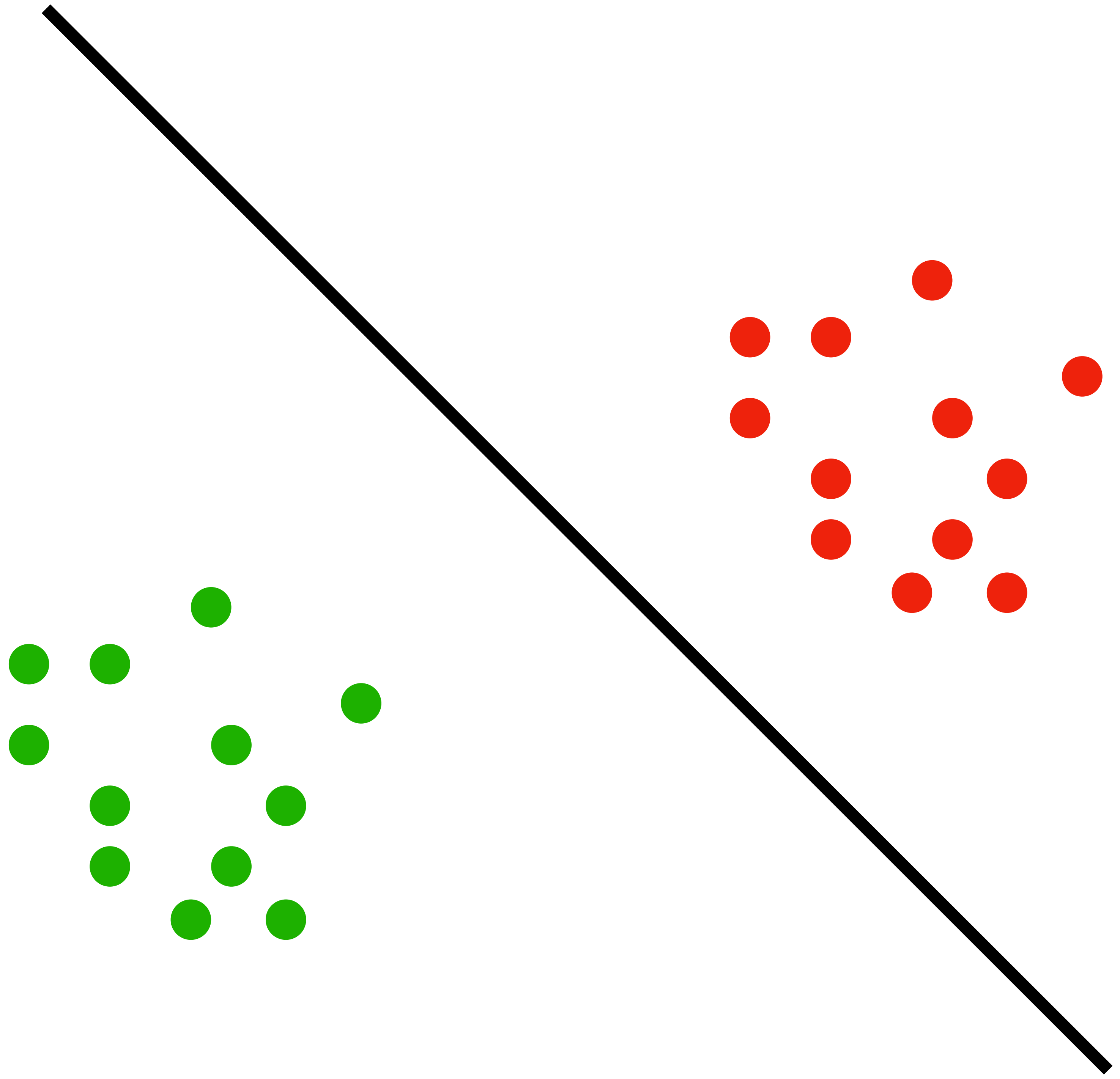
Classifiers

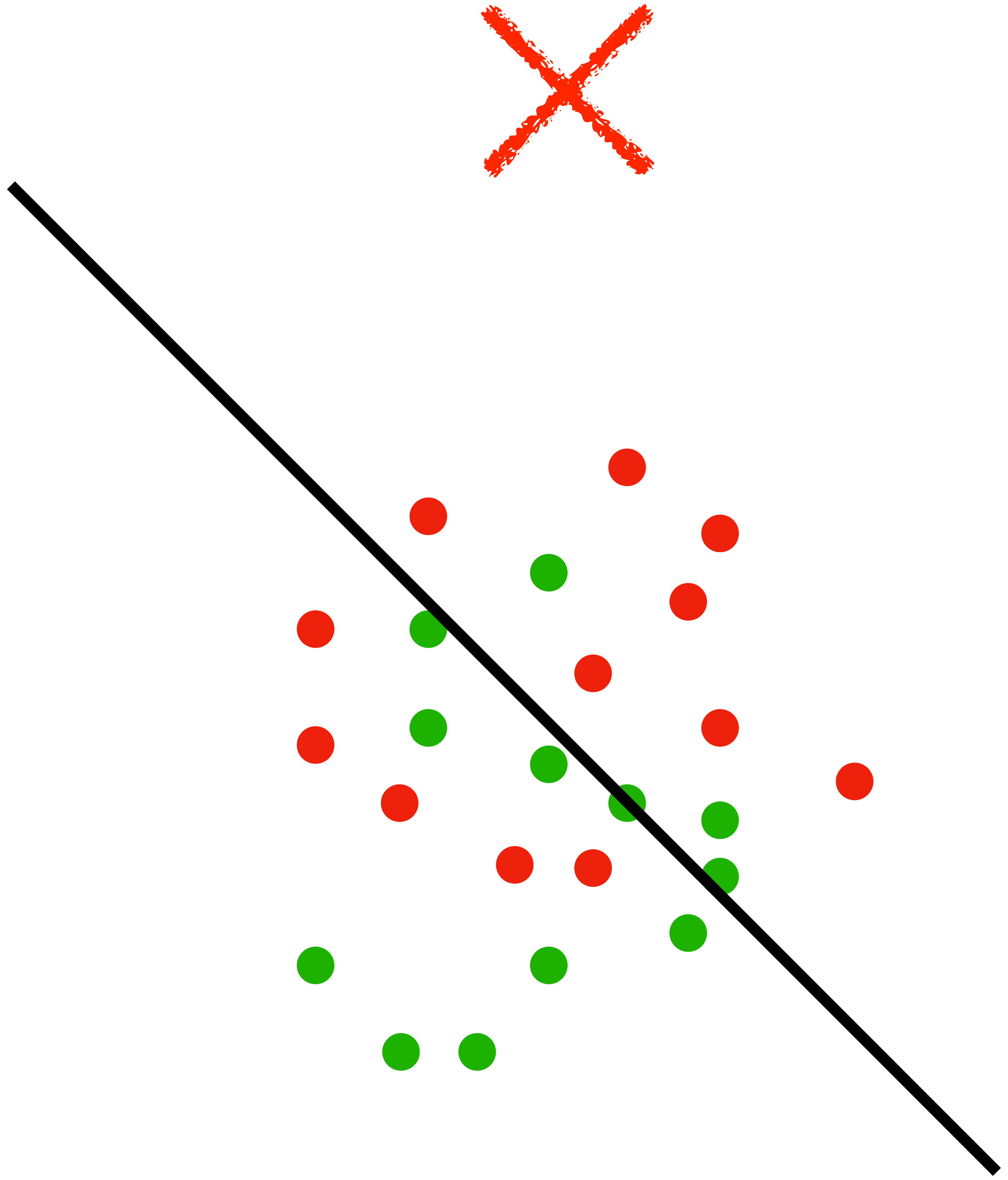


$$y_j = f(w_j x_j + b_j)$$



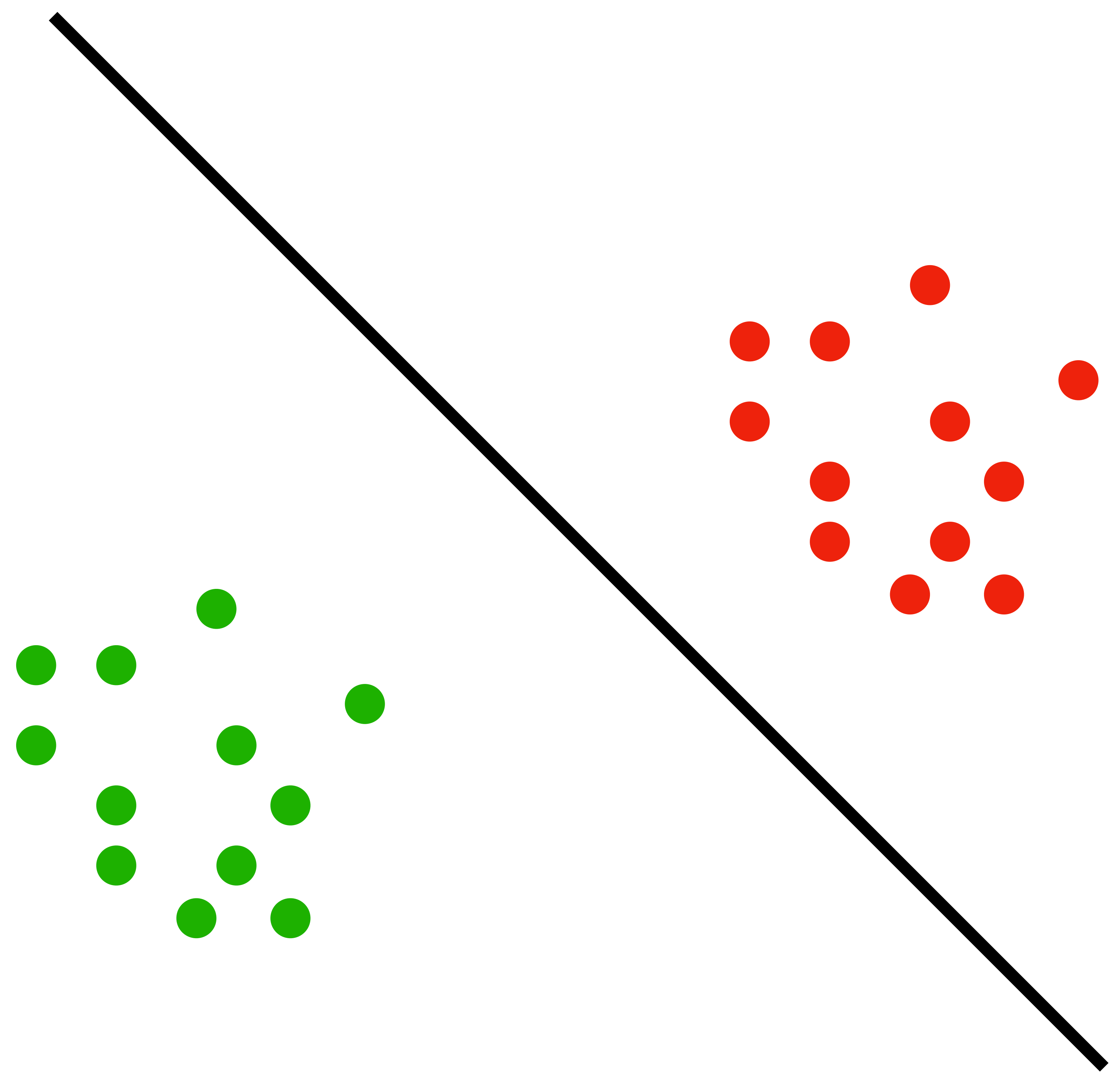
Classifiers



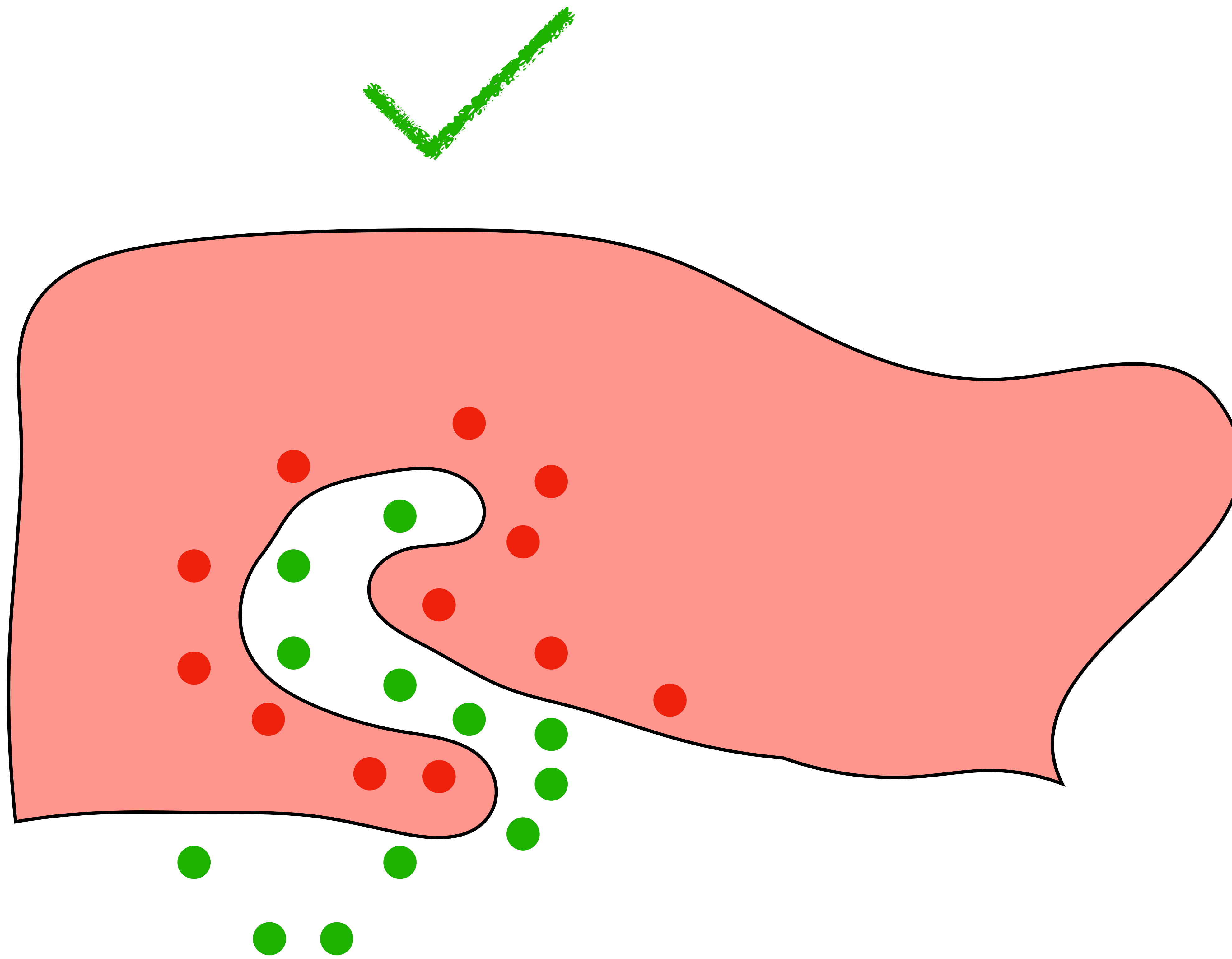


$$y_j = f(w_j x_j + b_j)$$

Complex Classifiers



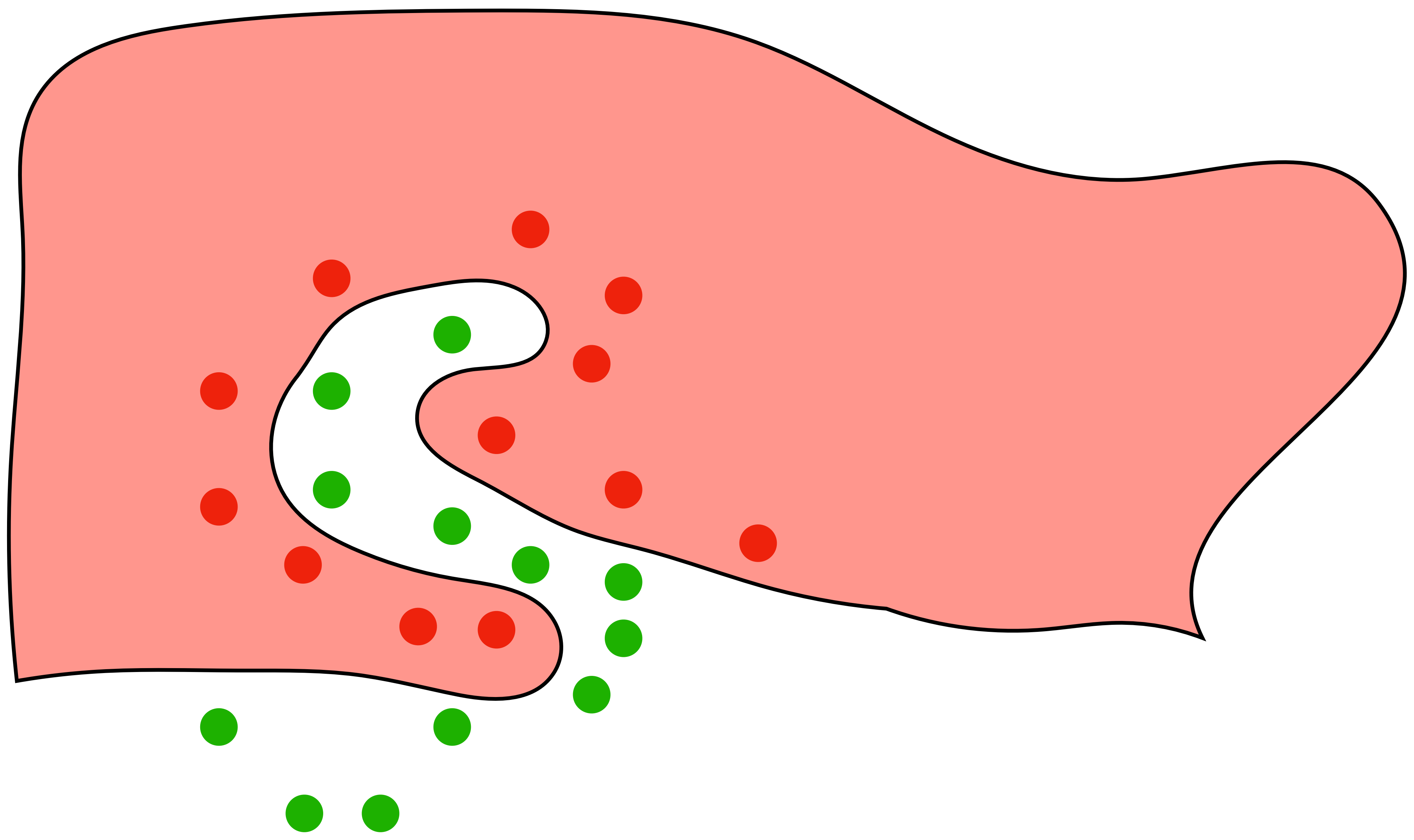
$$y_j = f(w_j x_j + b_j)$$



Complex classifier

Complex Classifiers

Complex classifier



What features can produce this decision rule ?

Perceptron Classifier

x_1

x_2

x_3

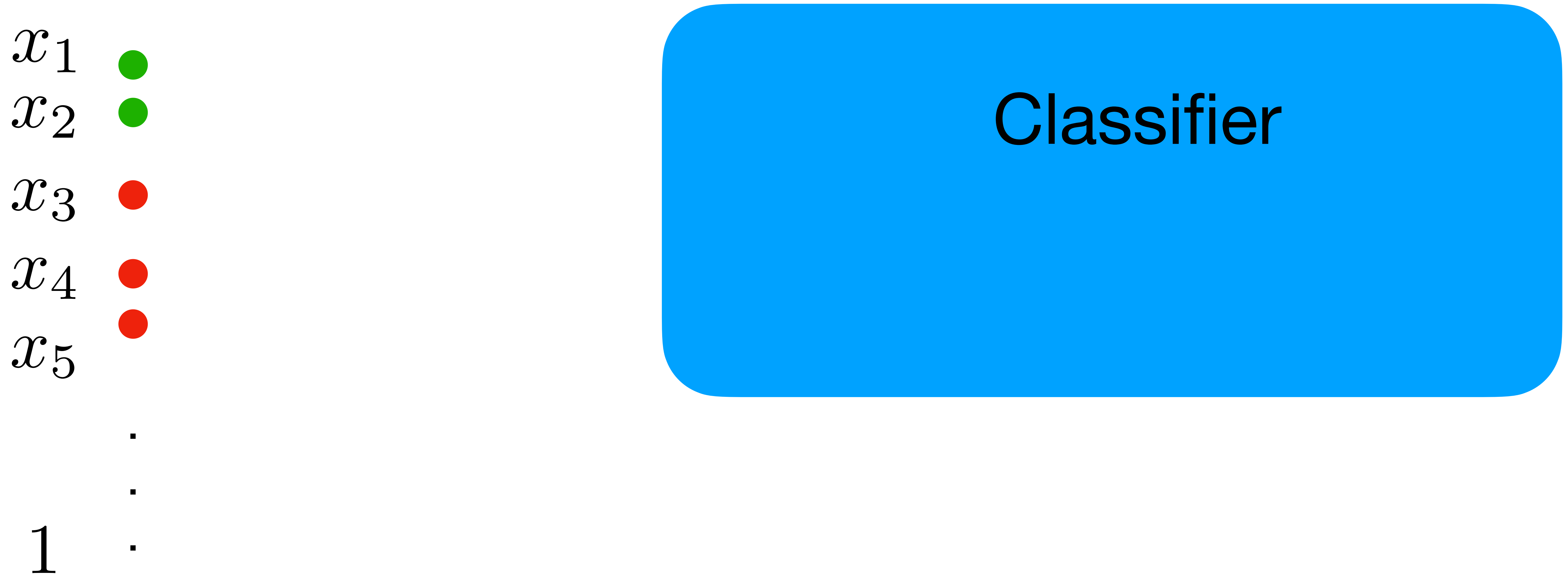
x_4

x_5

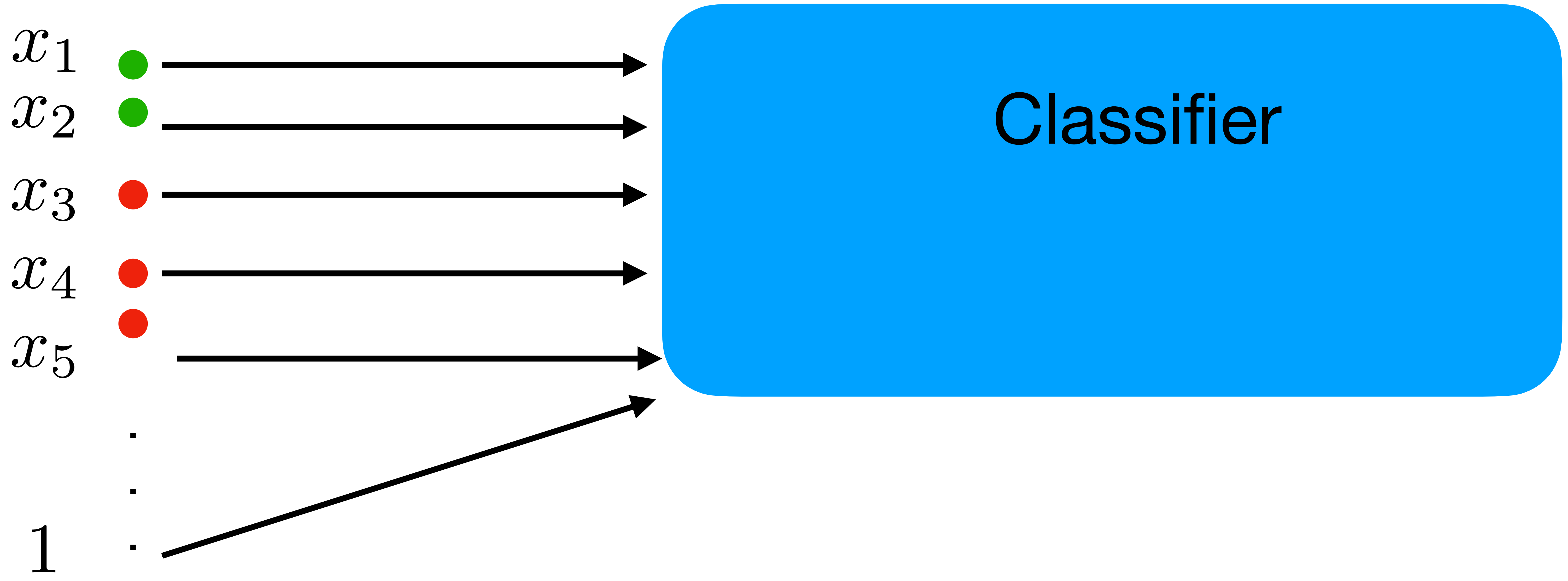
$\vdots$

1

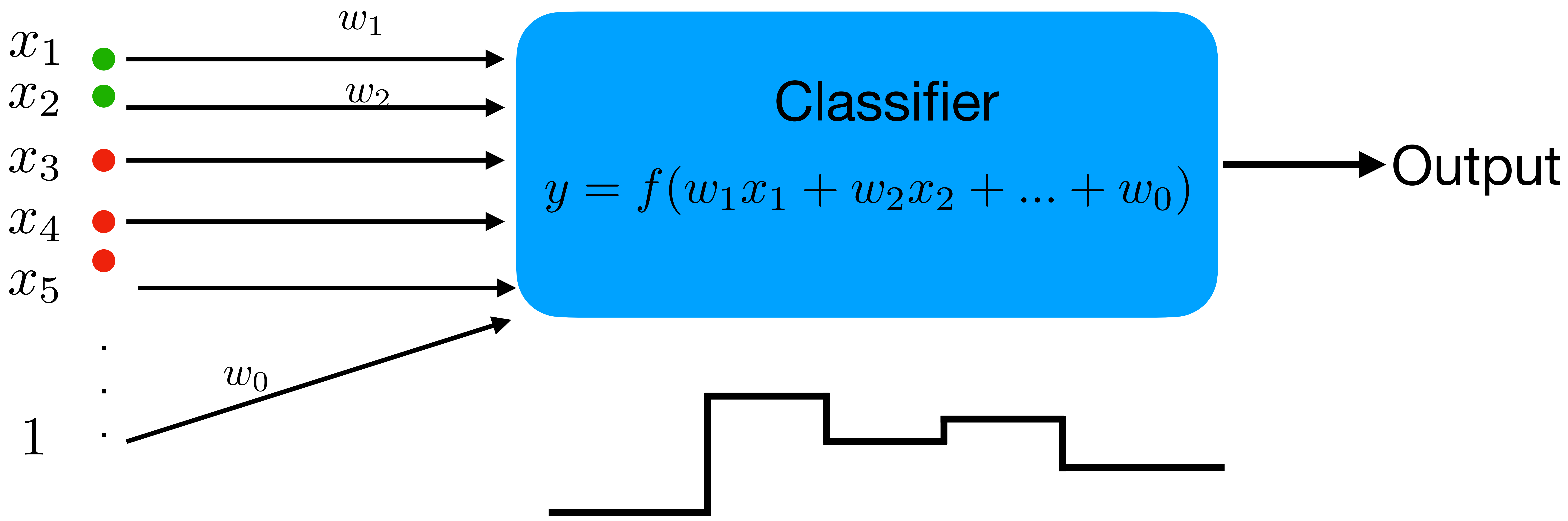
Perceptron Classifier



Perceptron Classifier



Perceptron Classifier

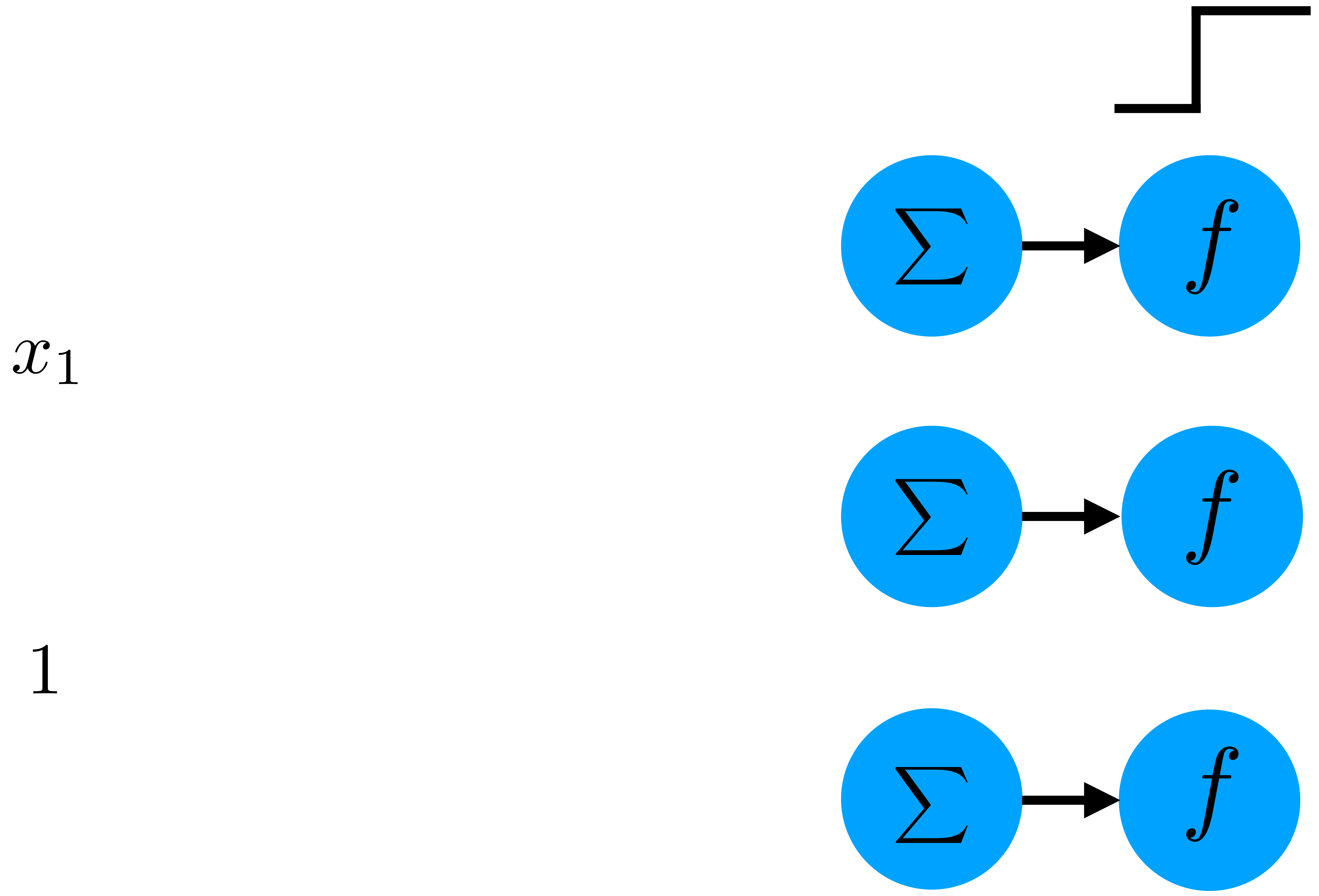


Multi-layer Perceptron

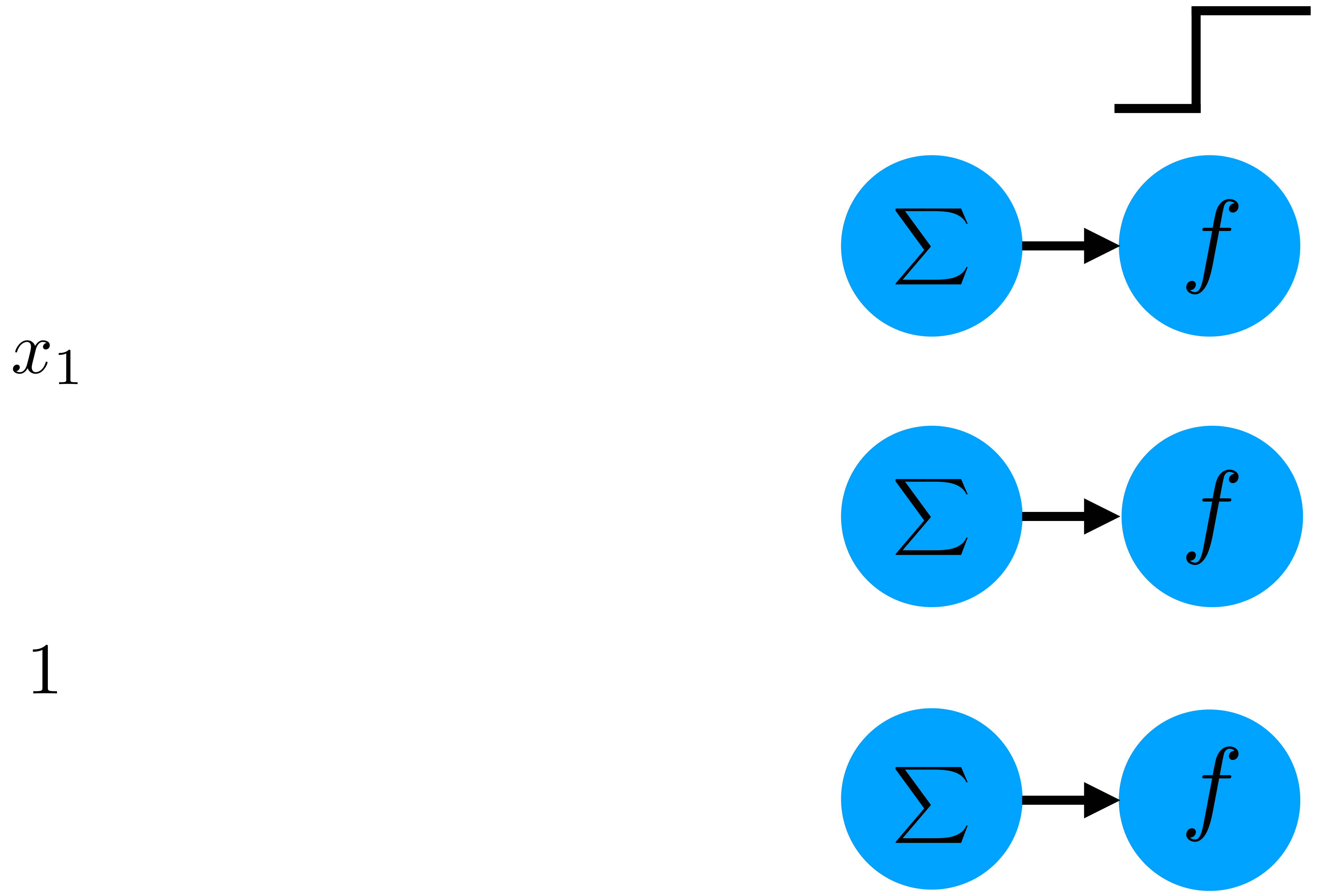
x_1

1

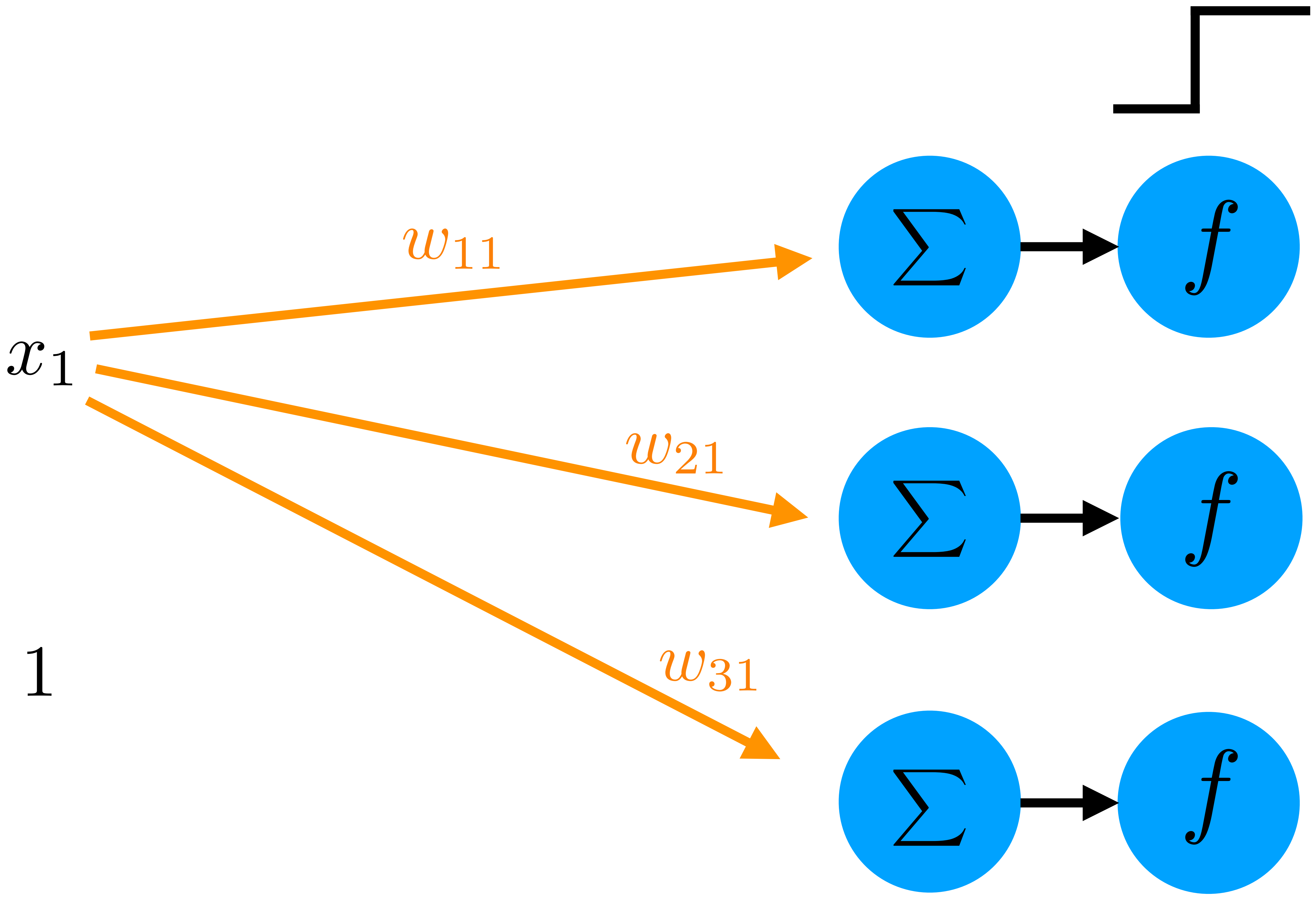
Multi-layer Perceptron



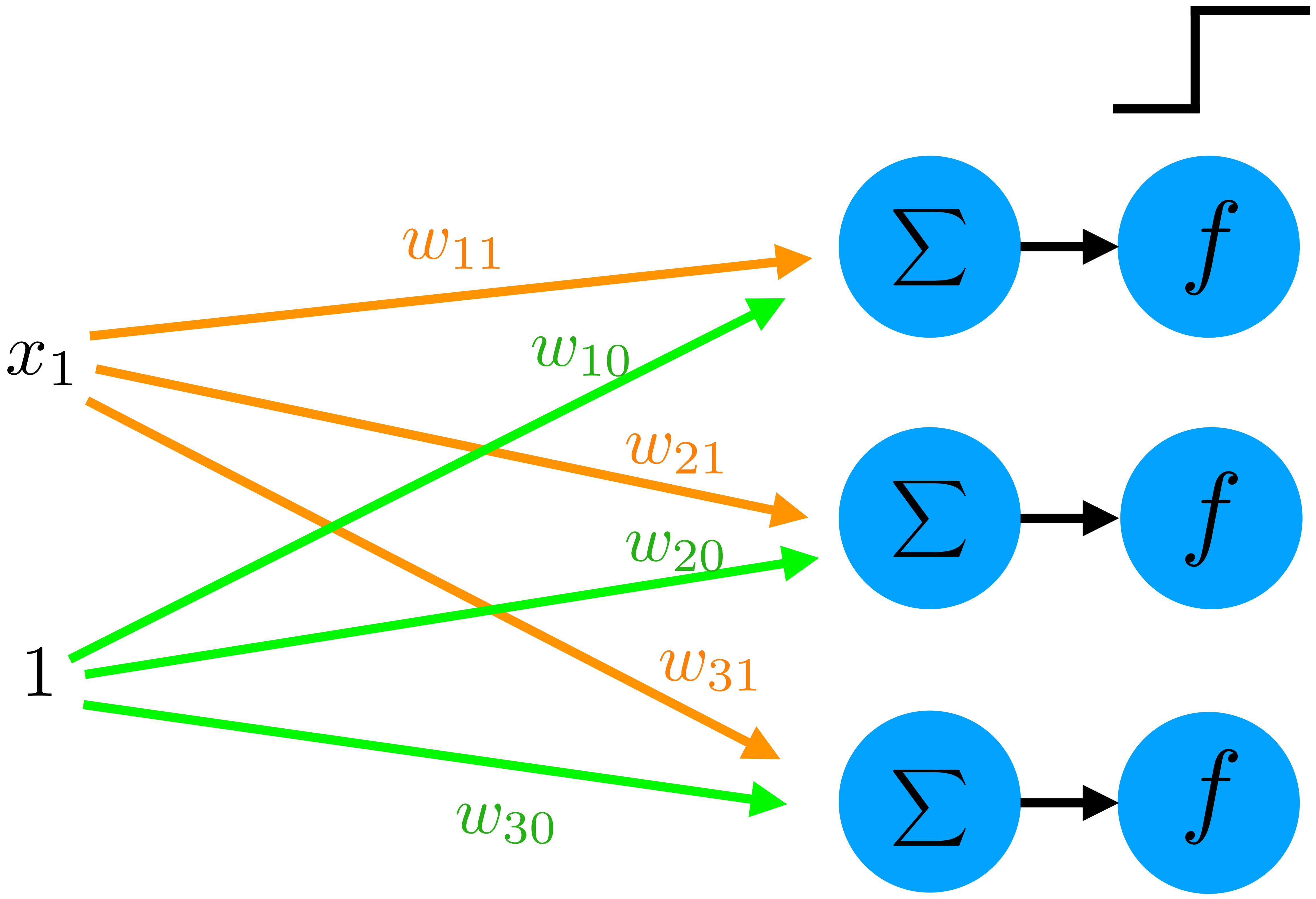
Multi-layer Perceptron



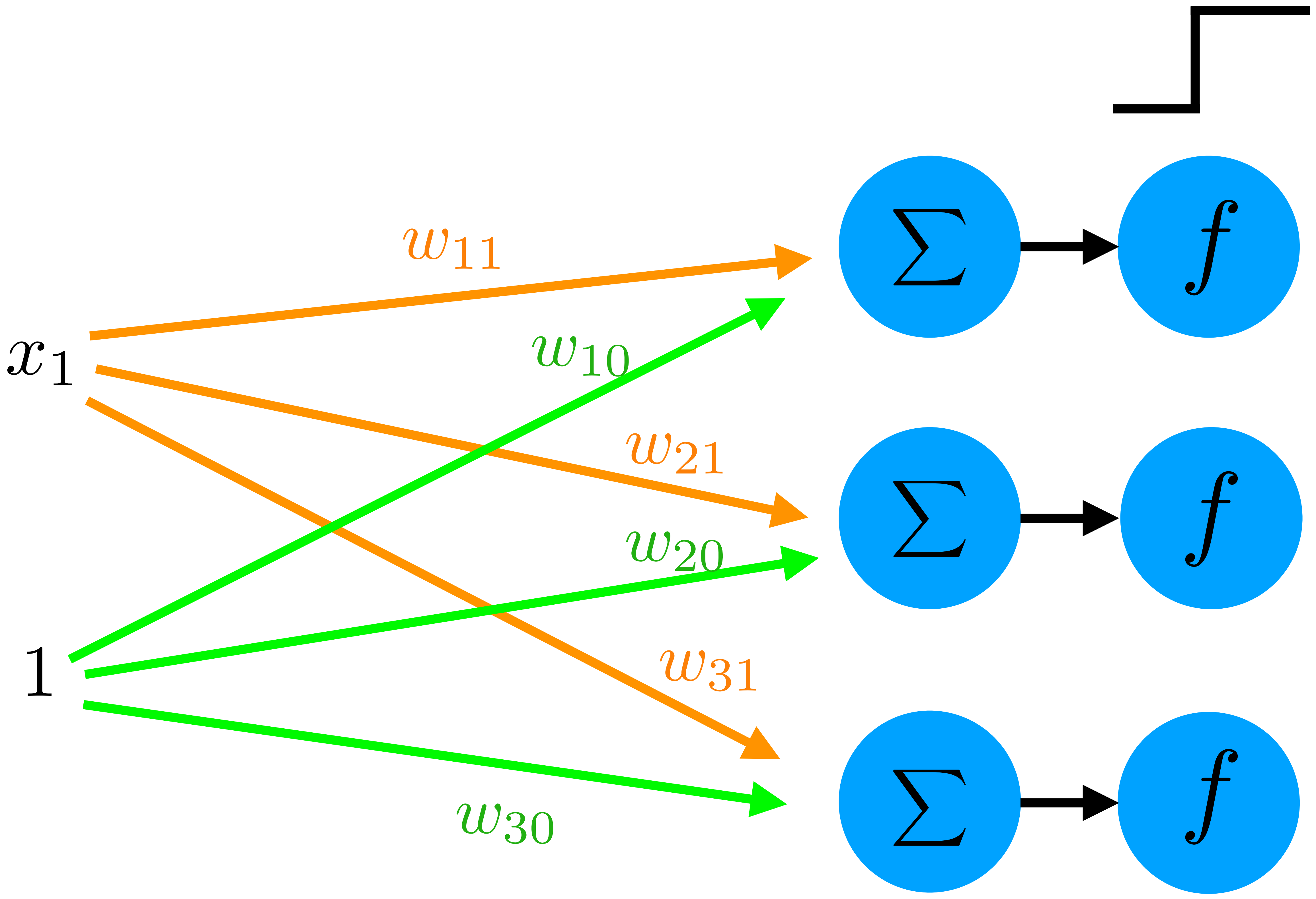
Multi-layer Perceptron



Multi-layer Perceptron



Multi-layer Perceptron

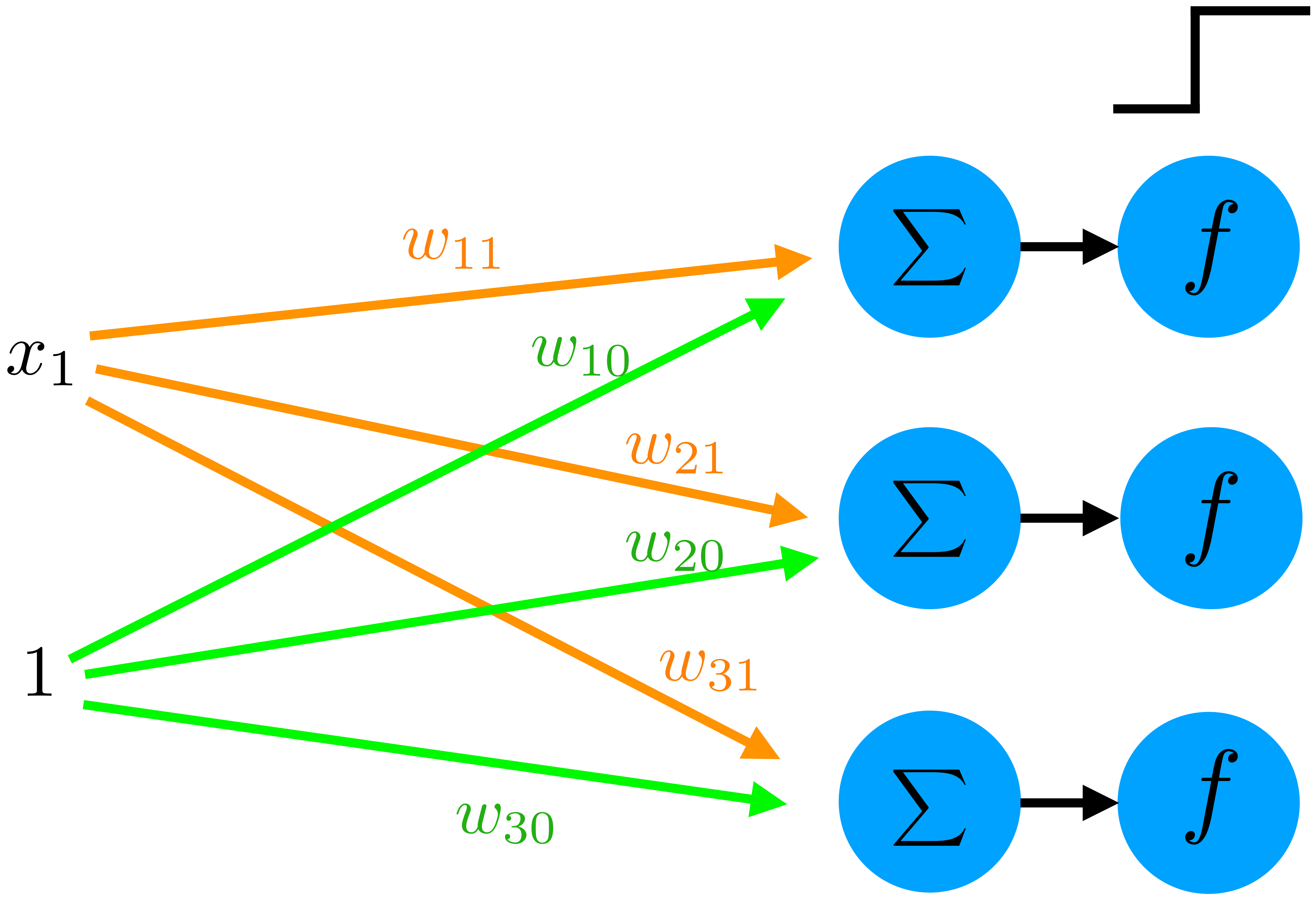


$x_1\, w_{11} + w_{10}$

$x_1\, w_{21} + w_{20}$

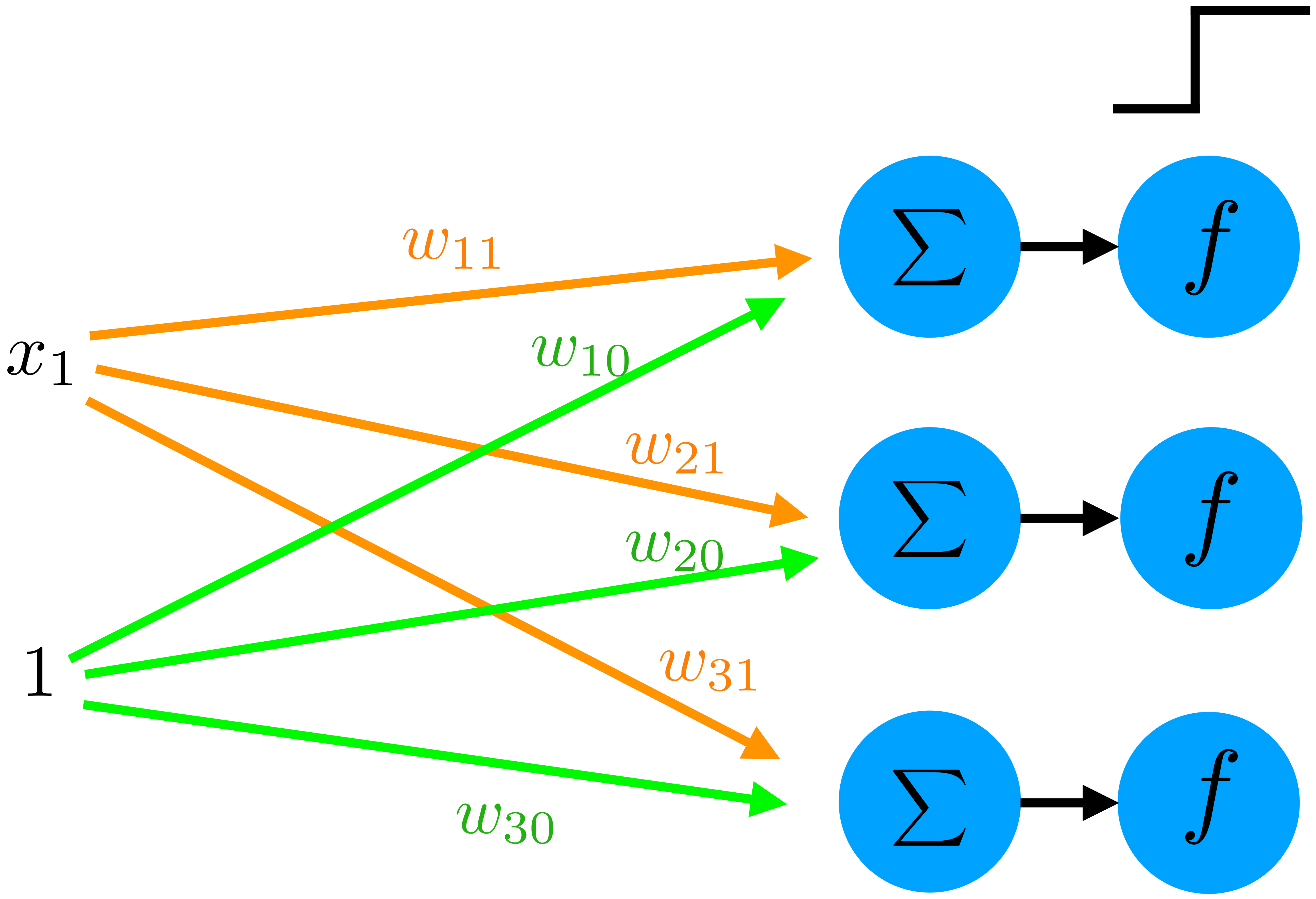
$x_1\, w_{31} + w_{30}$

Multi-layer Perceptron



$$y_1 = f(x_1 w_{11} + w_{10})$$
$$y_2 = f(x_1 w_{21} + w_{20})$$
$$y_3 = f(x_1 w_{31} + w_{30})$$

Multi-layer Perceptron



$$y_1 = f(x_1 w_{11} + w_{10})$$
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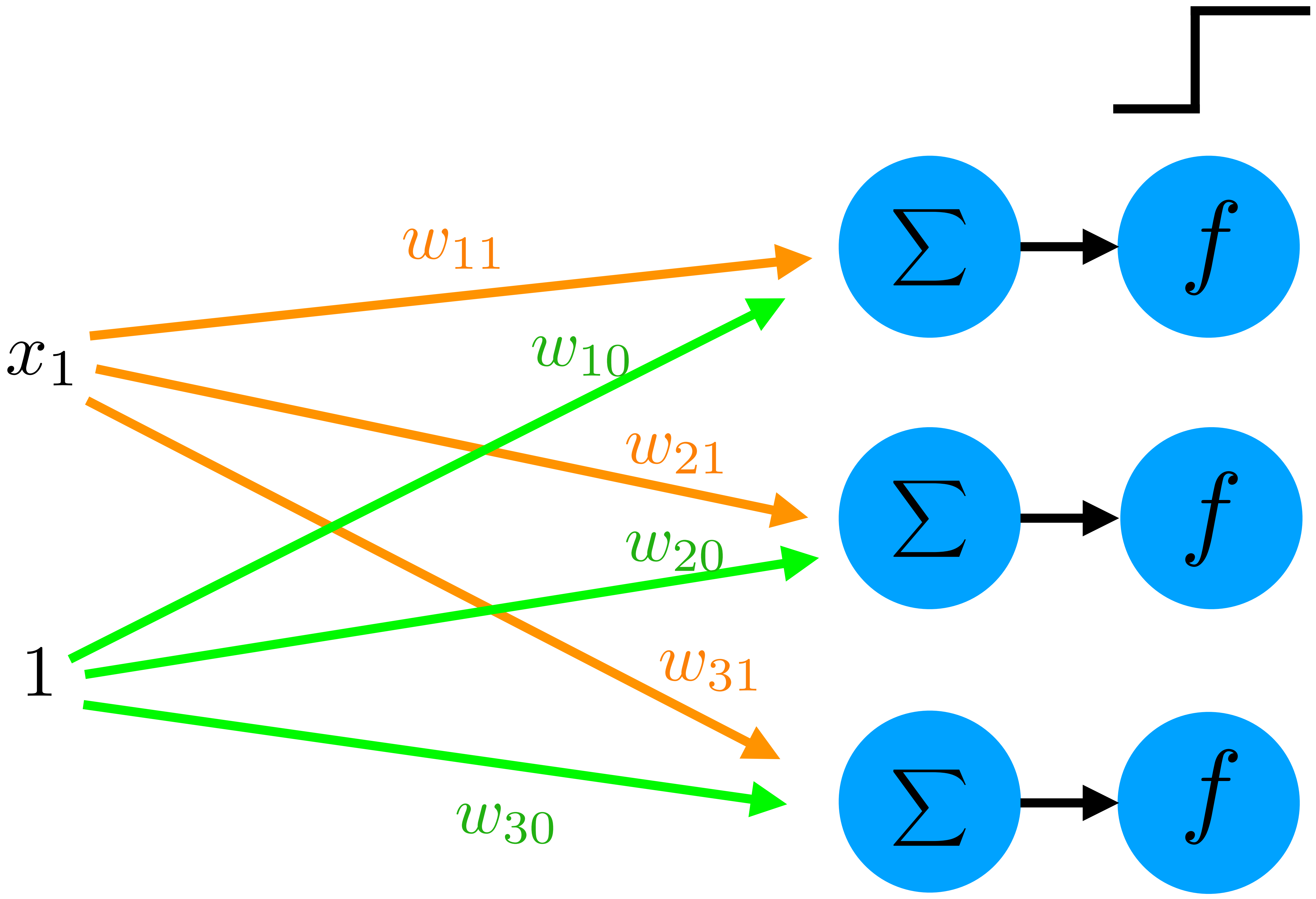
Multi-layer Perceptron



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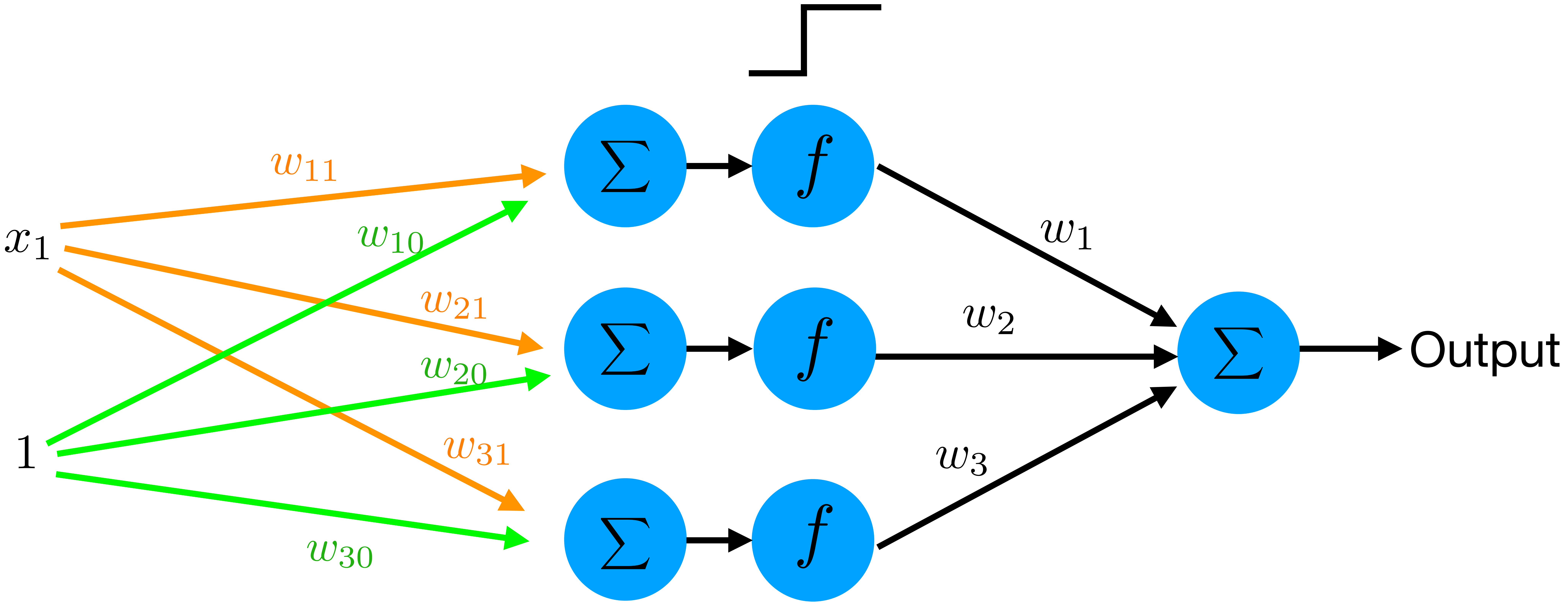
Multi-layer Perceptron



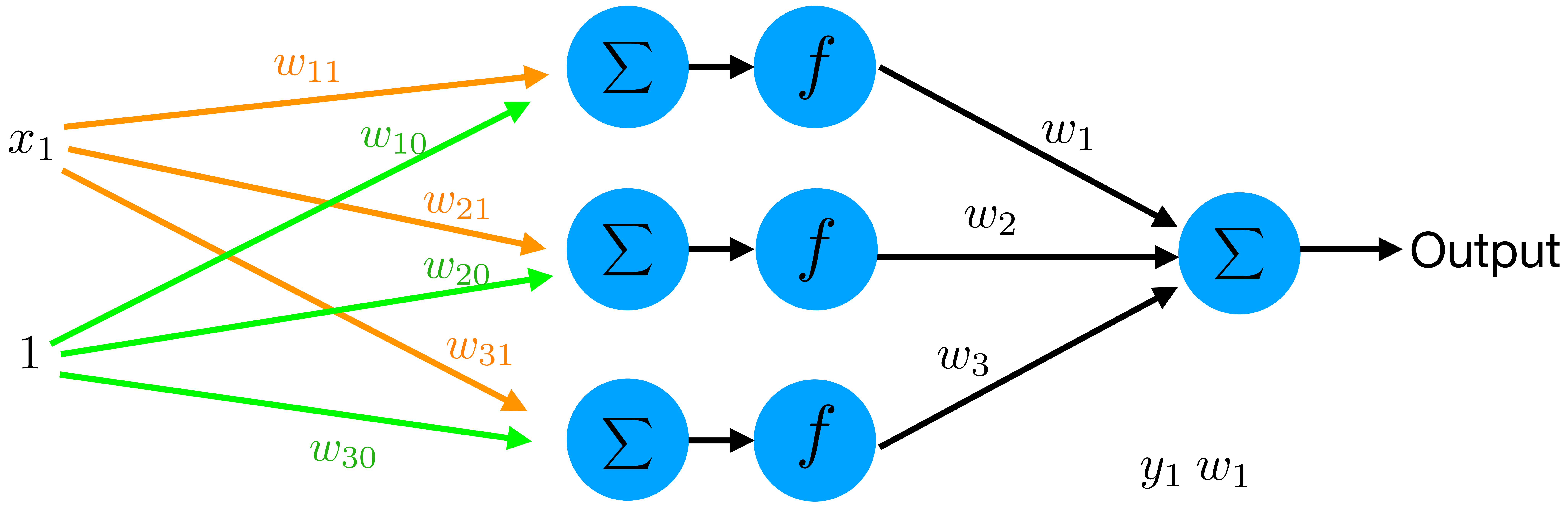
$y_1 = f(x_1 w_{11} + w_{10})$
$y_2 = f(x_1 w_{21} + w_{20})$
$y_3 = f(x_1 w_{31} + w_{30})$

Multi-layer Perceptron

Input features

Hidden layers

Output layers



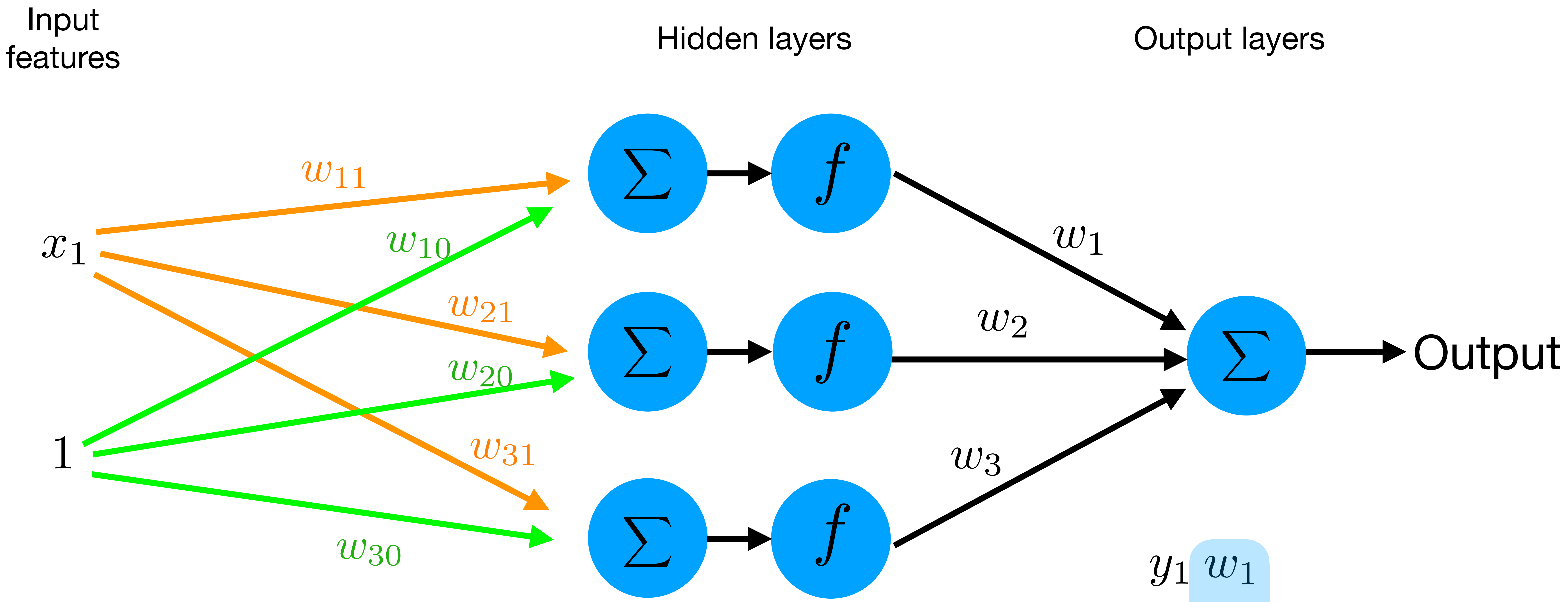
$$y_1 = f(x_1 w_{11} + w_{10})$$
$$y_2 = f(x_1 w_{21} + w_{20})$$
$$y_3 = f(x_1 w_{31} + w_{30})$$

$y_1 \; w_1$

$y_2 \; w_2$

$y_3 \; w_3$

Multi-layer Perceptron



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Multi-layer Perceptron

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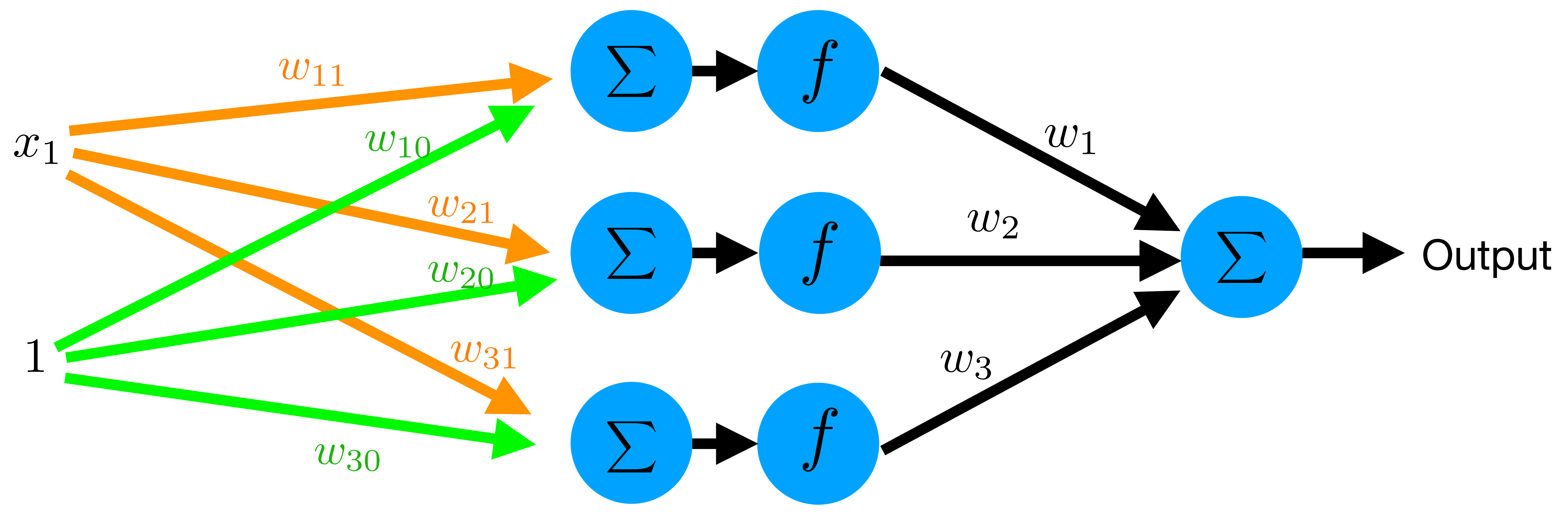


"Features" are outputs of perceptrons

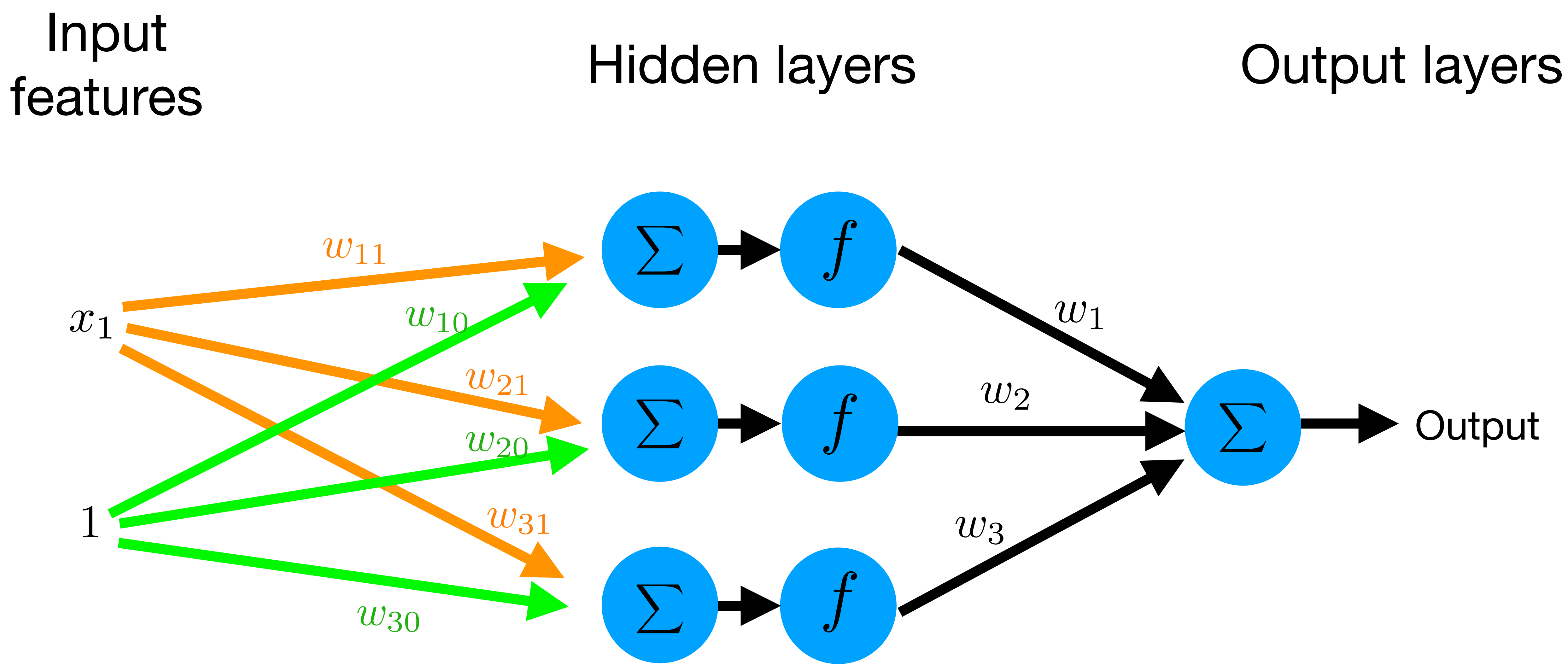
Matrix of first layer weights

$$\begin{matrix} w_{11} & w_{10} \\ w_{21} & w_{20} \\ w_{31} & w_{30} \end{matrix}$$

Matrix of second layer weights

$$\begin{matrix} w_1 \\ w_2 \\ w_3 \end{matrix}$$

Multi-layer Perceptron



"Features" are outputs of perceptrons

Matrix of first layer weights

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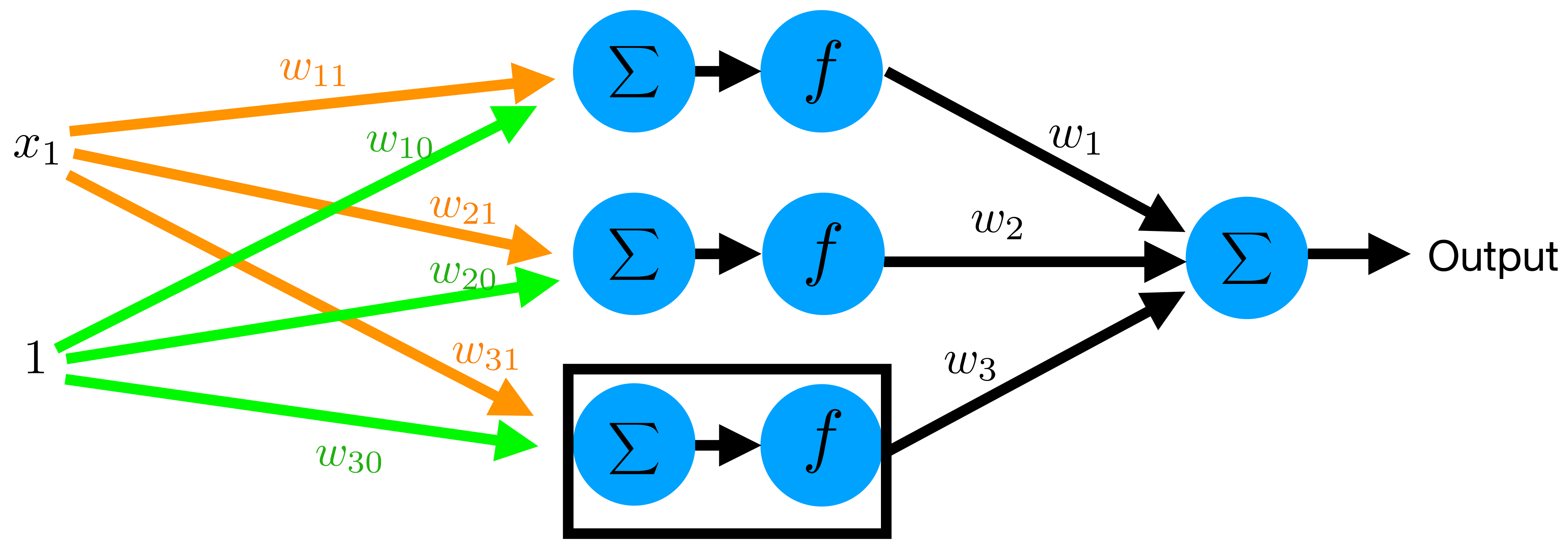
Multi-layer Perceptron

Input features

Hidden layers

Output layers



Perceptrons

"Features" are outputs of perceptrons

Matrix of second layer weights

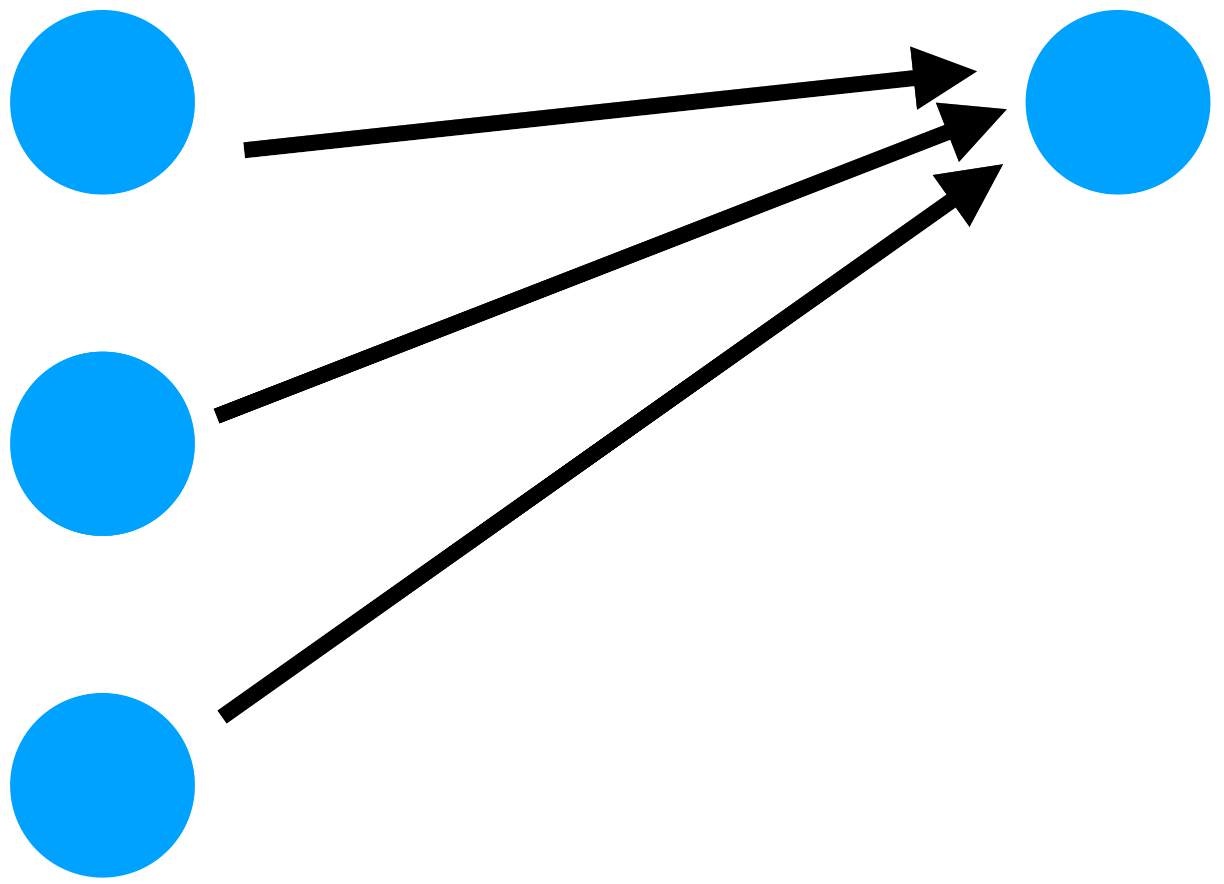
$$\begin{matrix} w_1 \\ w_2 \\ w_3 \end{matrix}$$

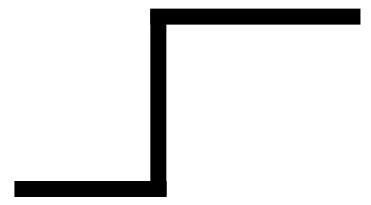
Matrix of first layer weights

$$\begin{matrix} w_{11} & w_{10} \\ w_{21} & w_{20} \\ w_{31} & w_{30} \end{matrix}$$

Features of MLPs

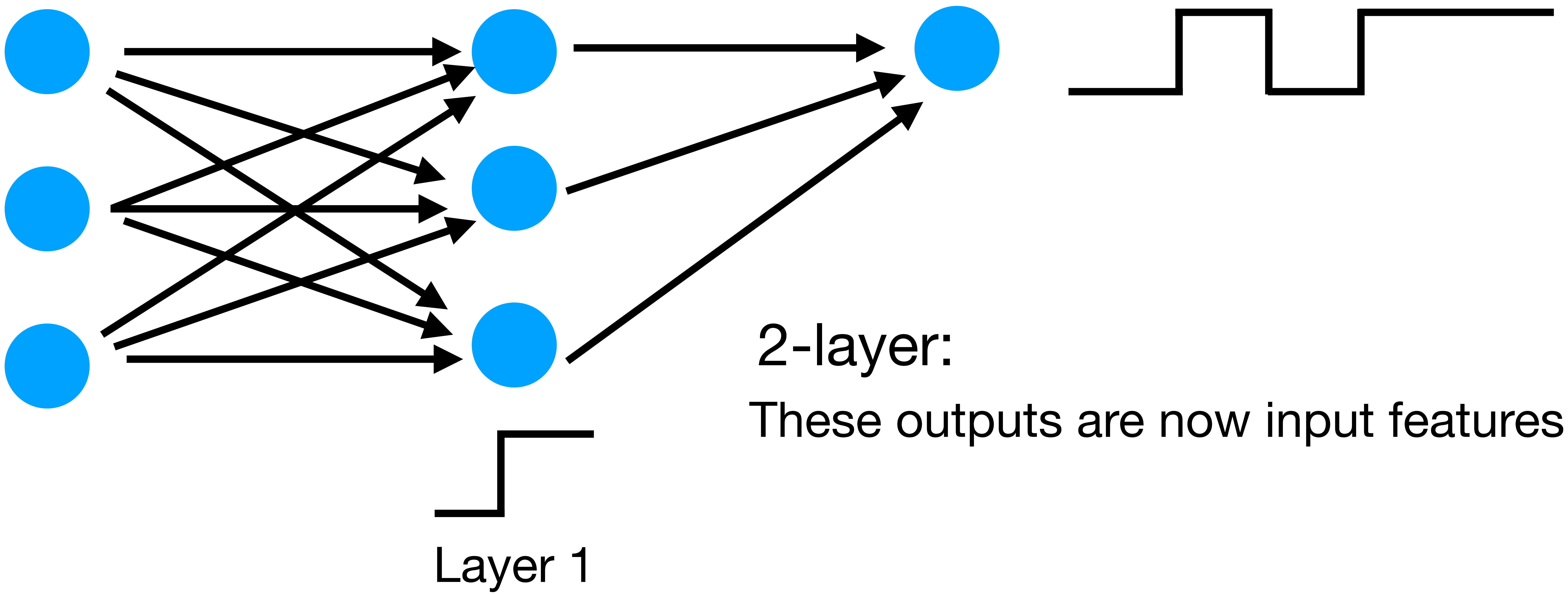
Input
features





Perceptron: Step function
with linear decision boundary

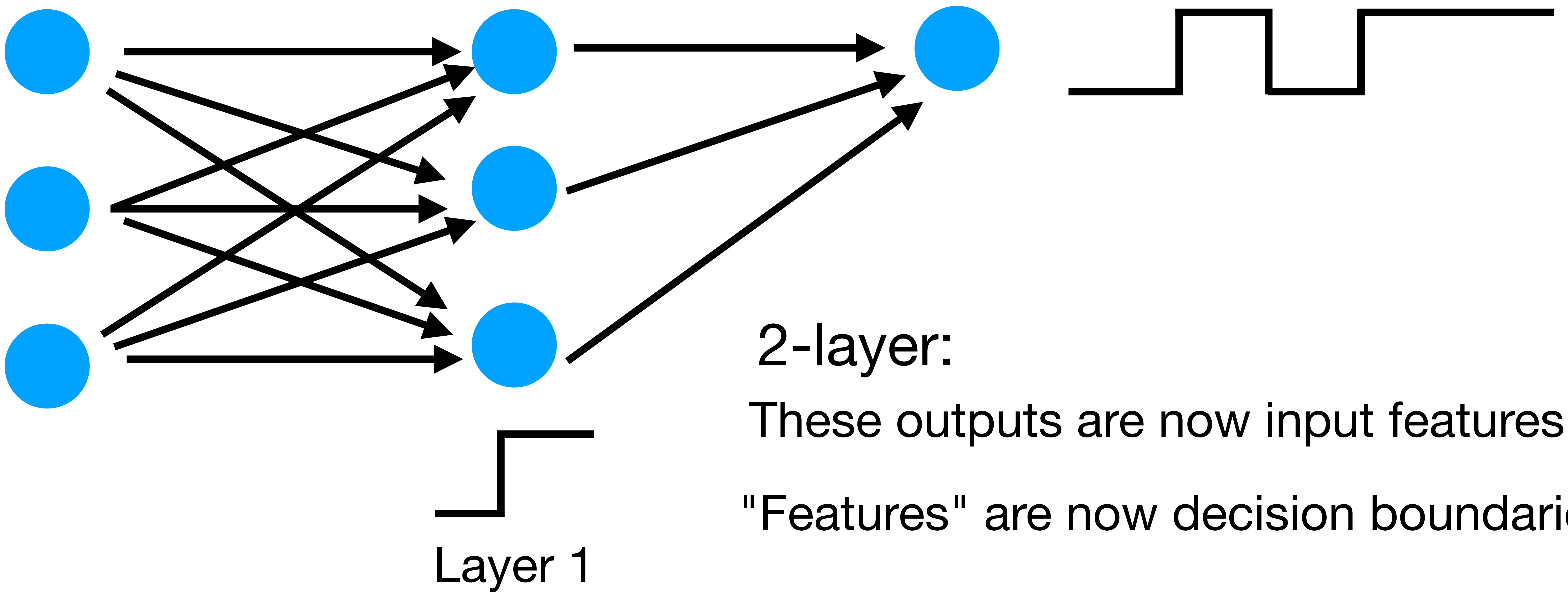
Features of MLPs



2-layer:

These outputs are now input features to the next layer

Features of MLPs

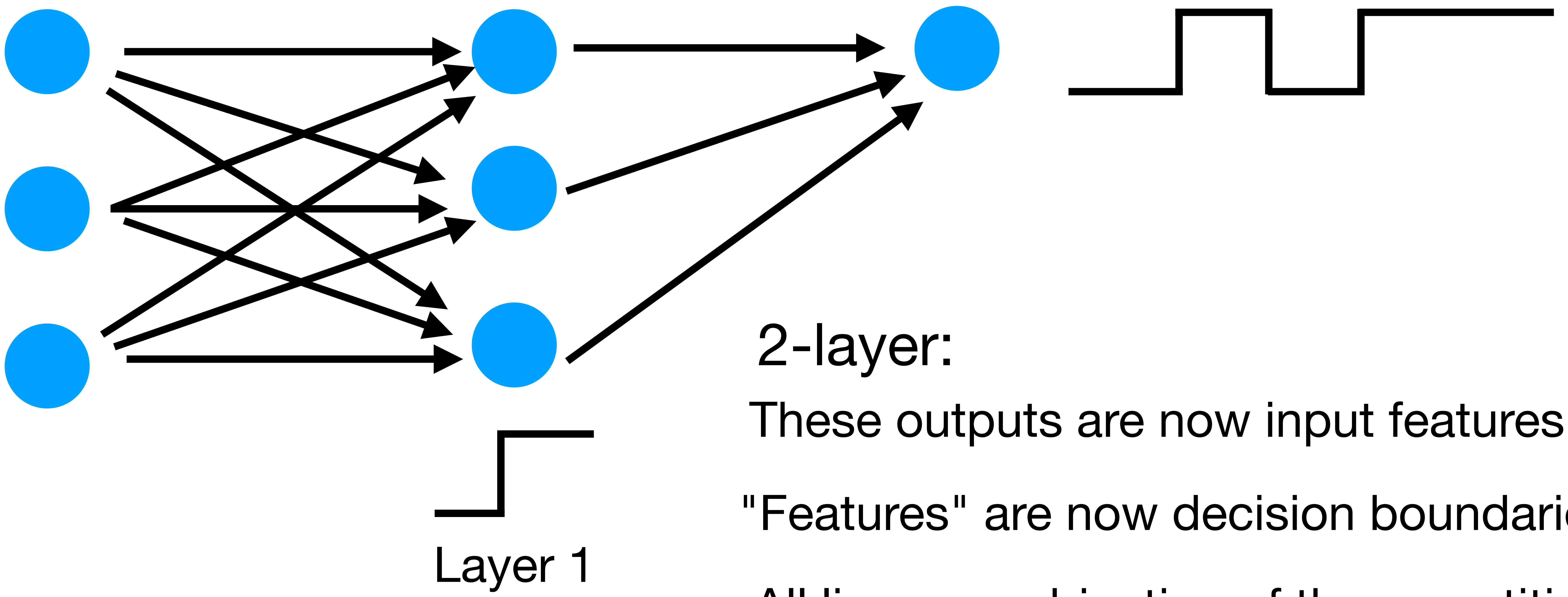


2-layer:

These outputs are now input features to the next layer

"Features" are now decision boundaries (partitions)

Features of MLPs



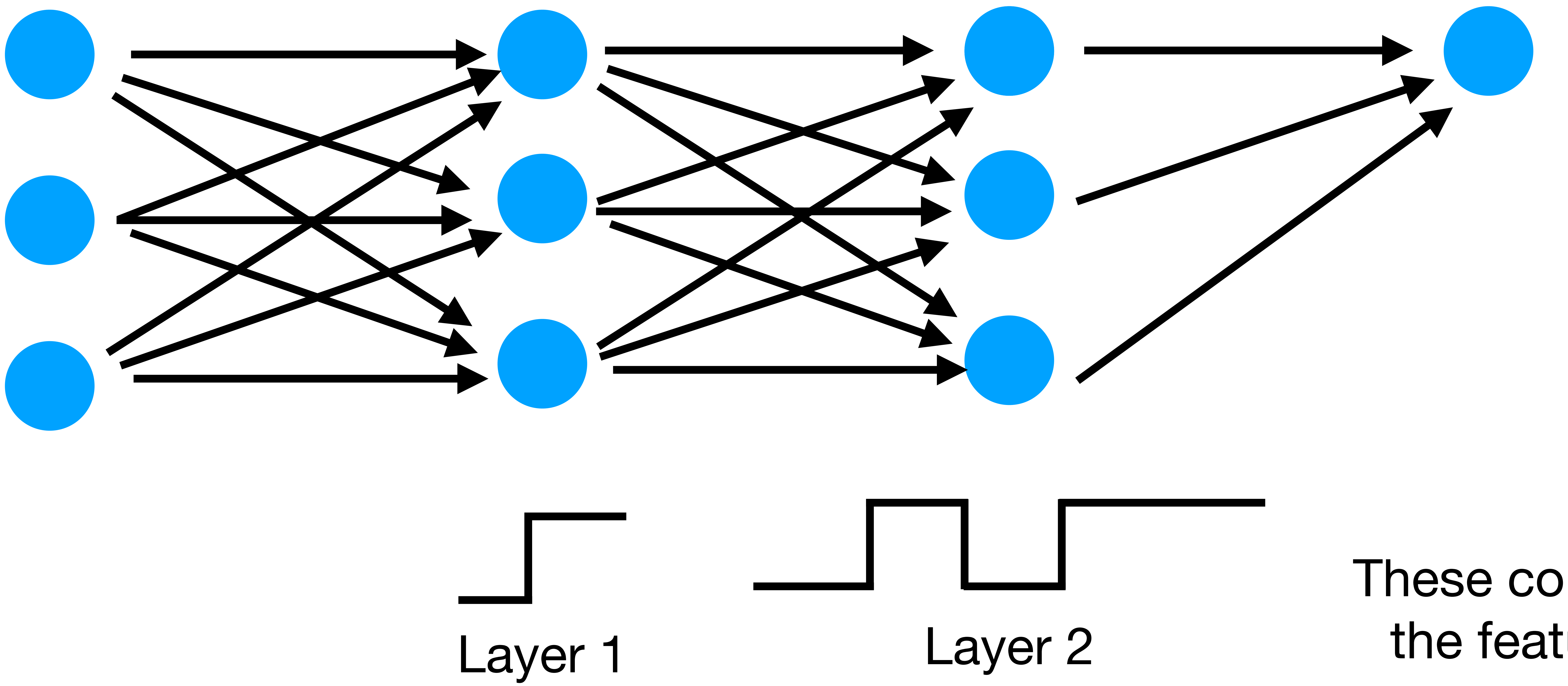
2-layer:

These outputs are now input features to the next layer

"Features" are now decision boundaries (partitions)

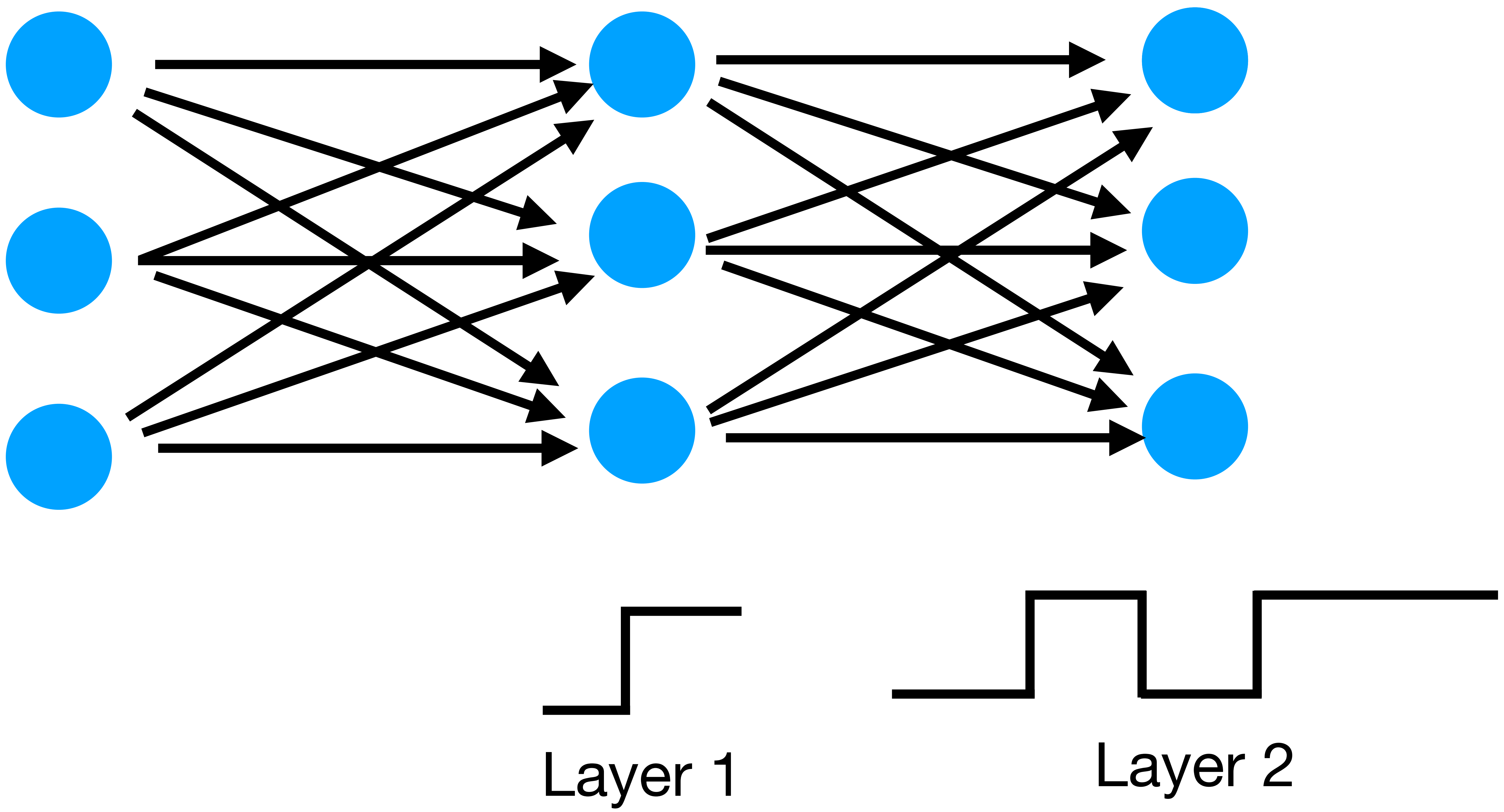
All linear combination of those partitions give complex partitions

Features of MLPs



These complex outputs become the features for the new layer

Features of MLPs



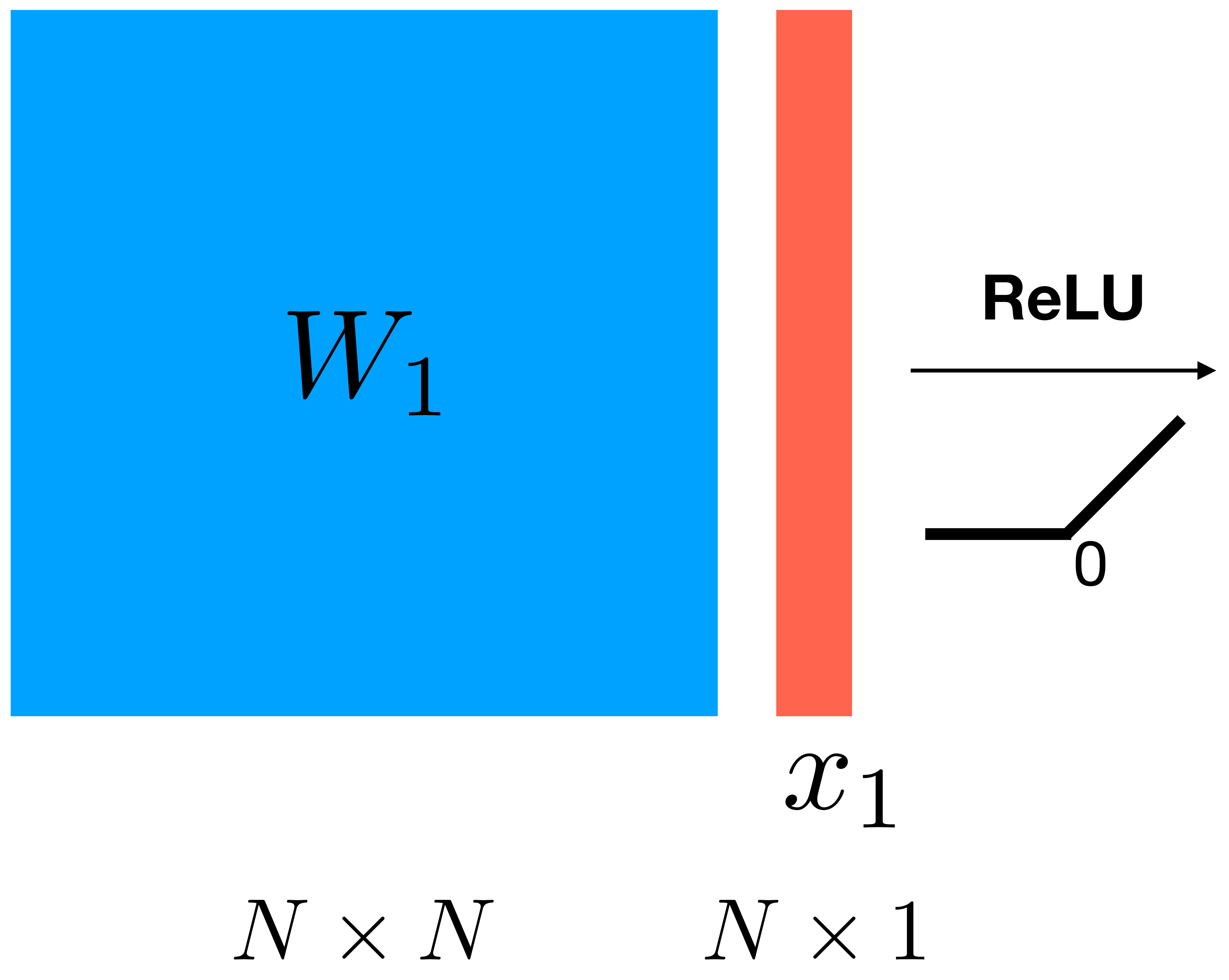
...

Deep Neural Networks

Computational Graph representation of Neural Networks

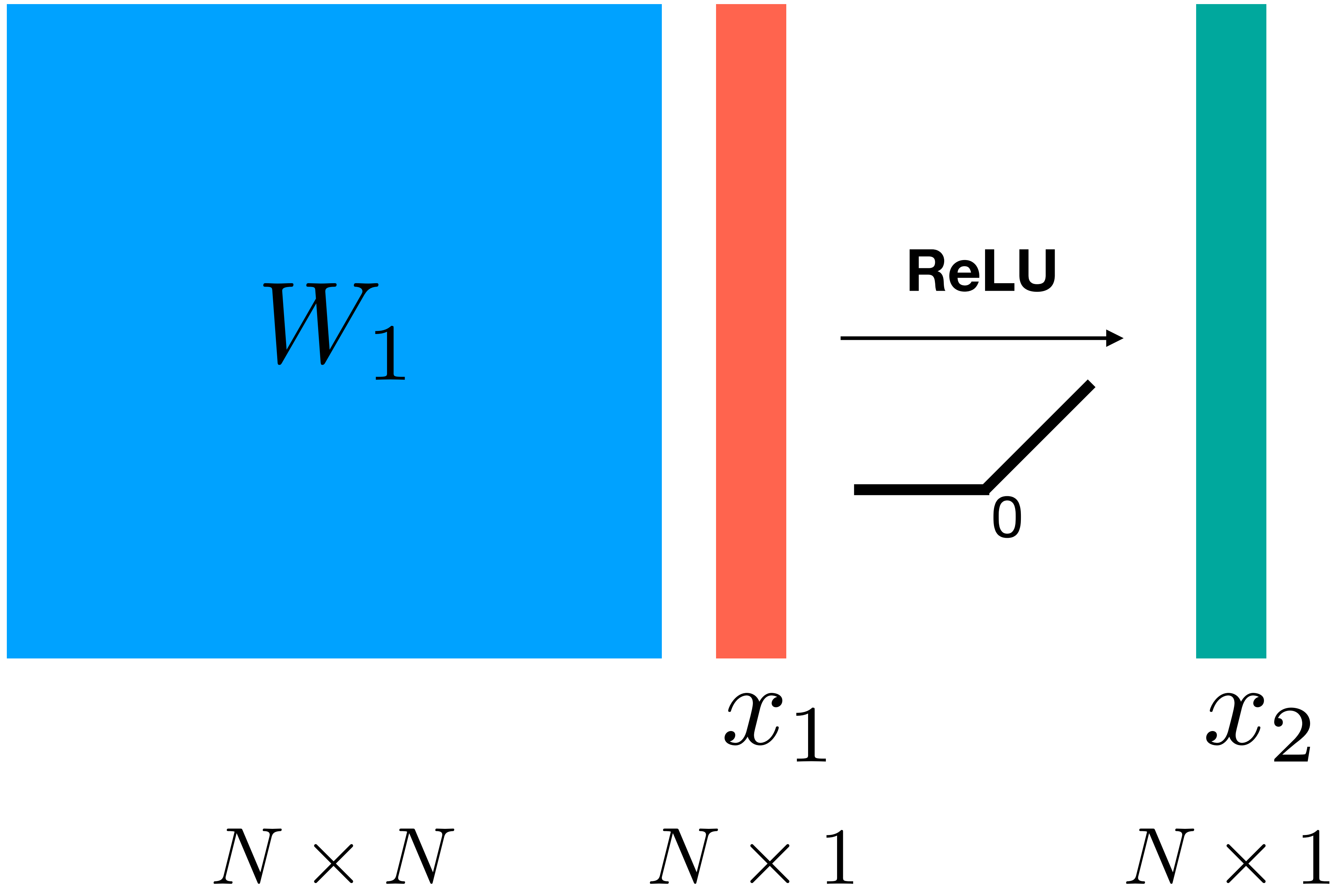
Neural Networks

Fully connected layers



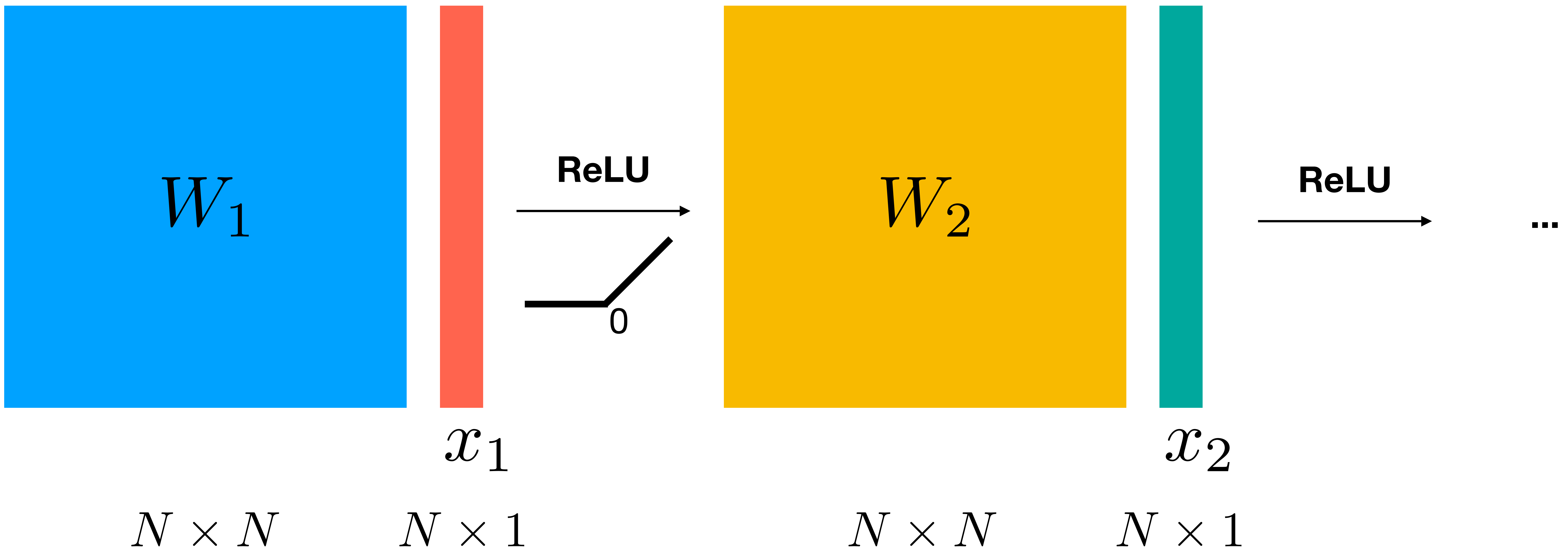
Neural Networks

Fully connected layers



Neural Networks

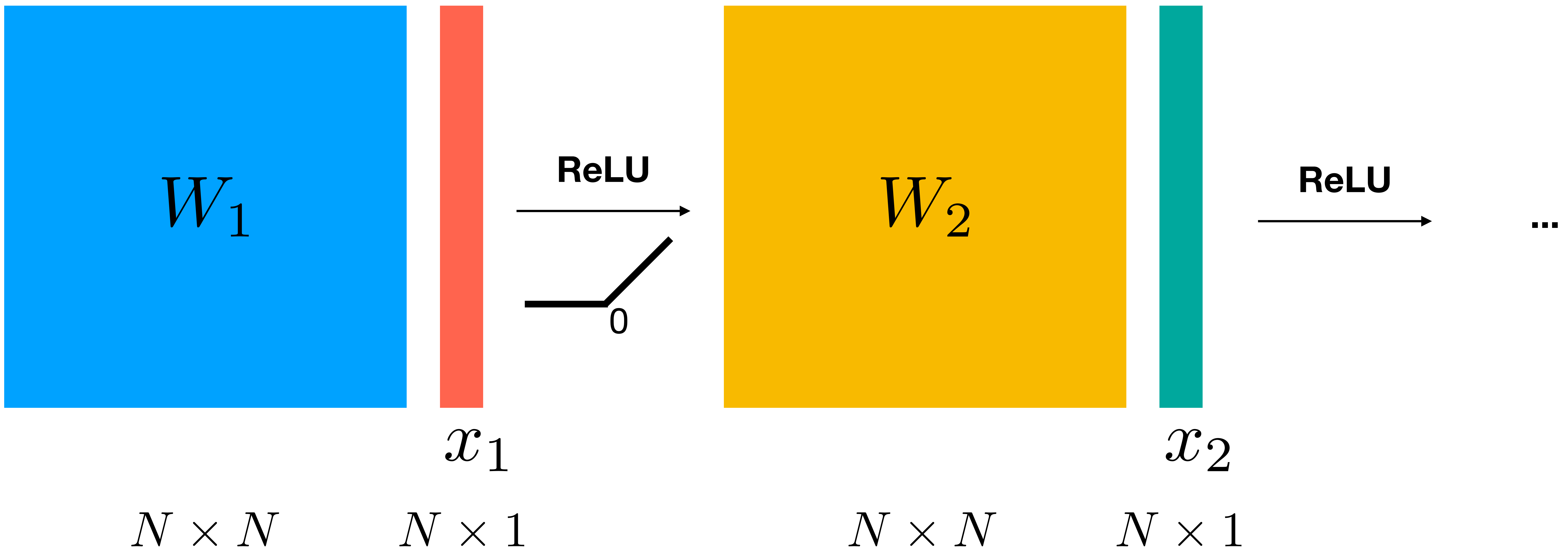
Fully connected layers



Neural Networks

data

Fully connected layers

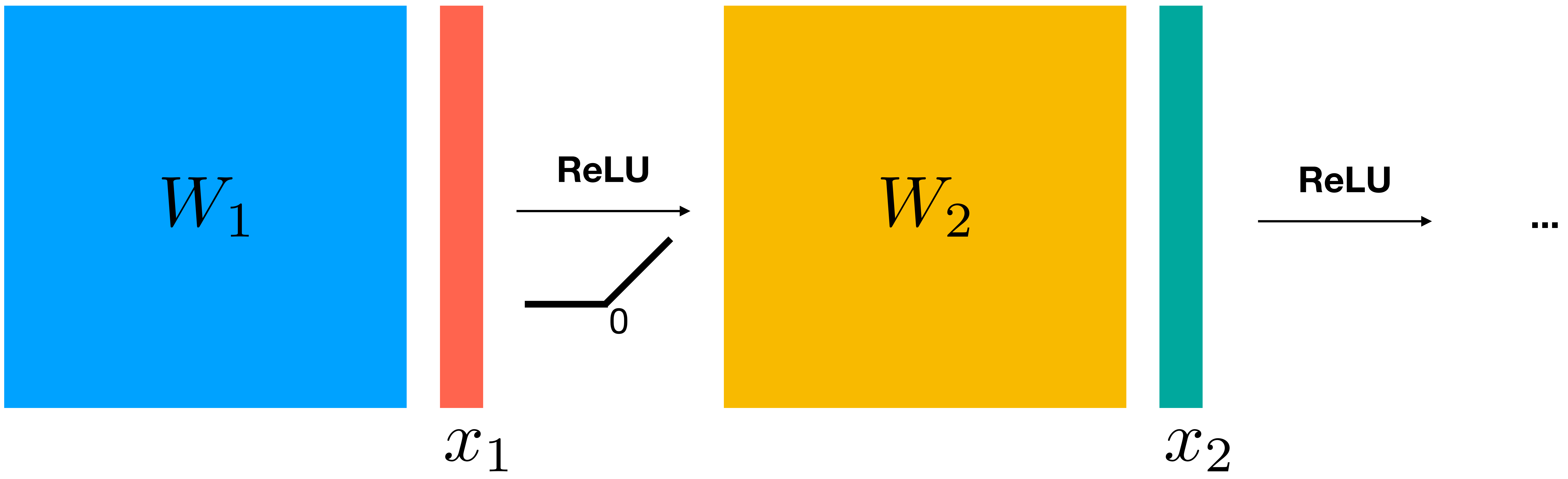


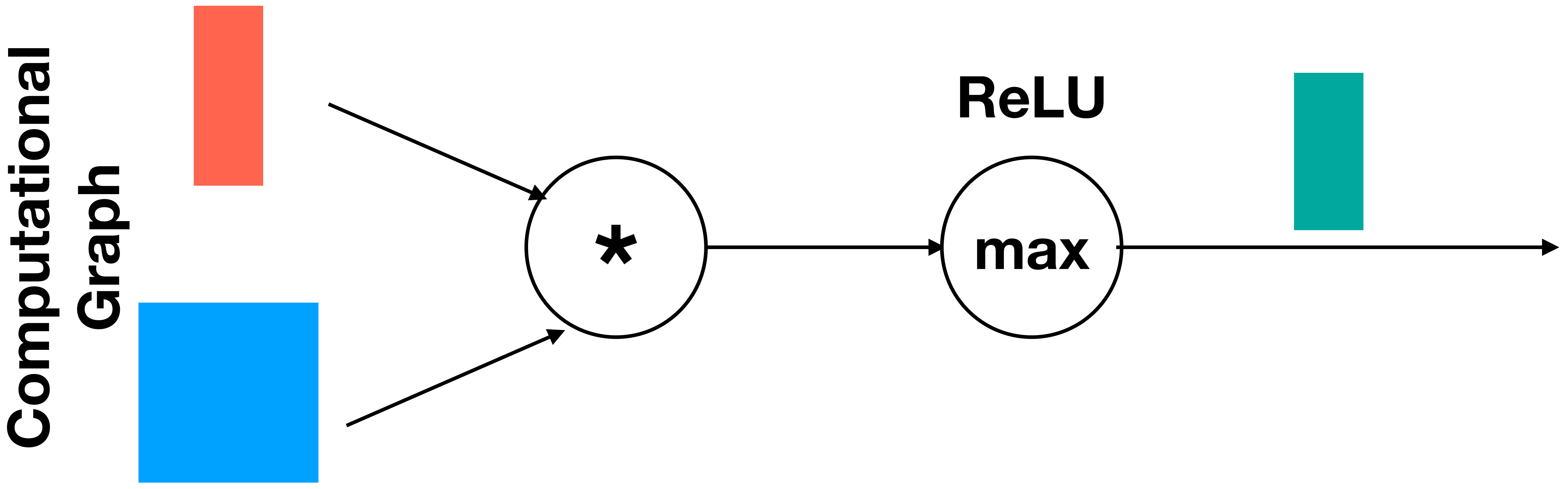
N represents number of pixels in an image

Neural Networks

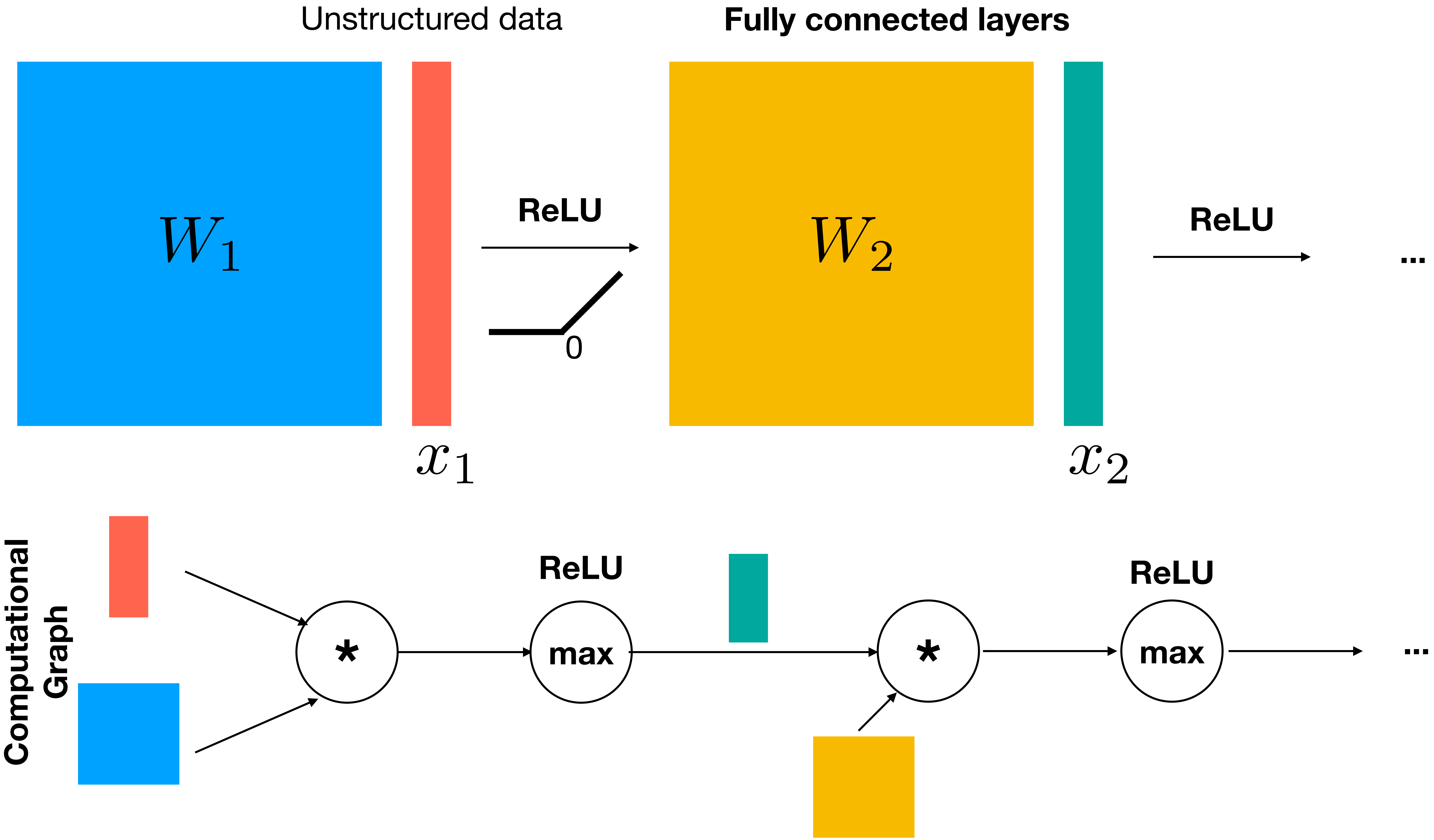
Unstructured data

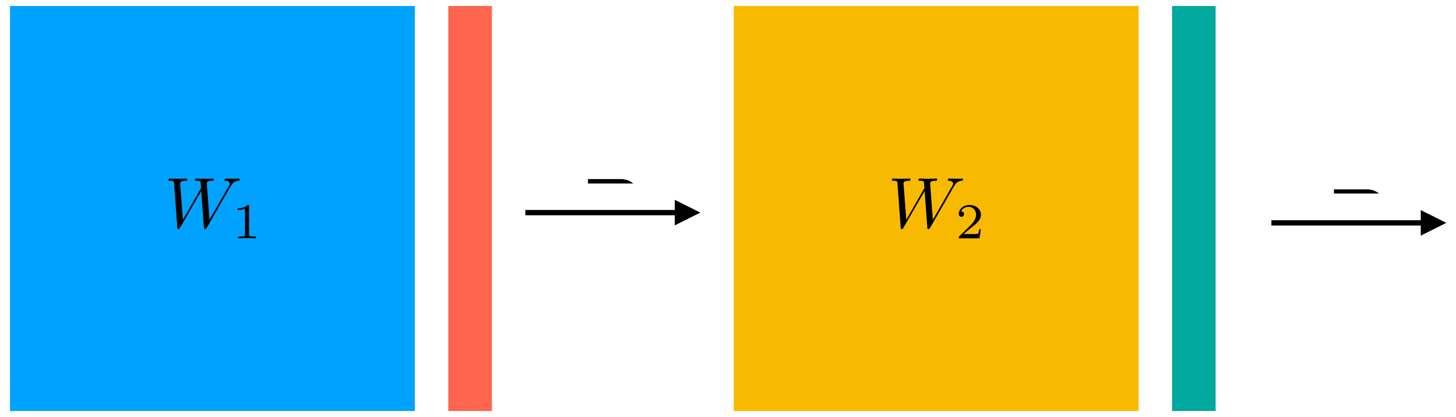
Fully connected layers





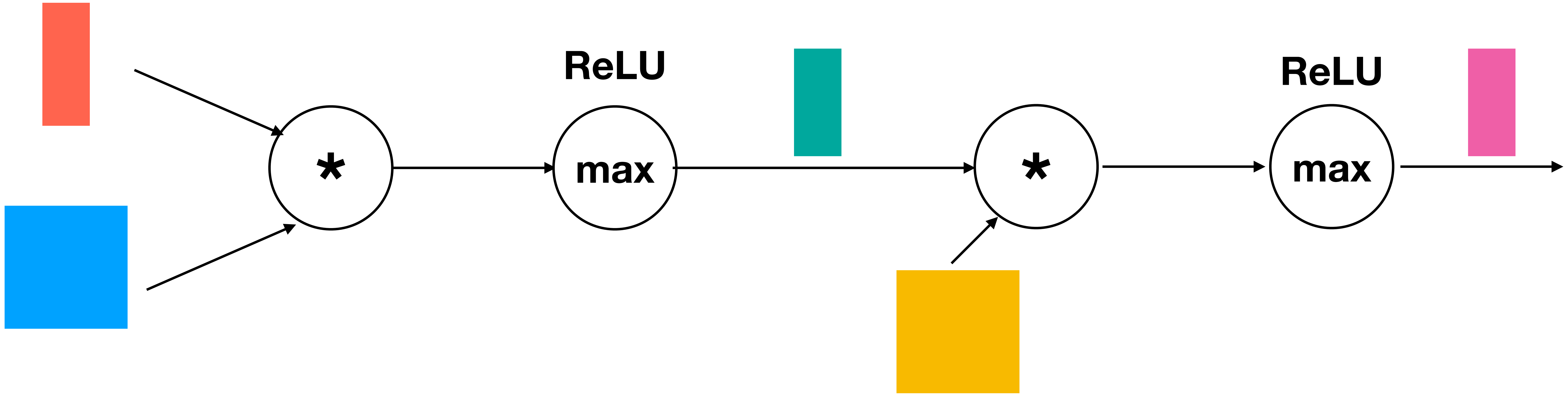
Neural Networks



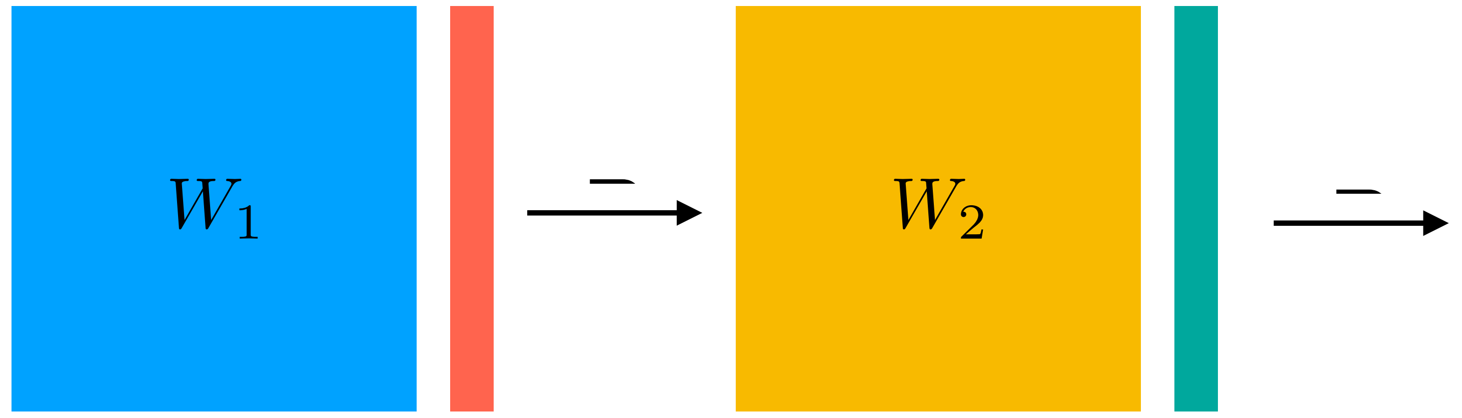


Two-layer model

Fully connected layers



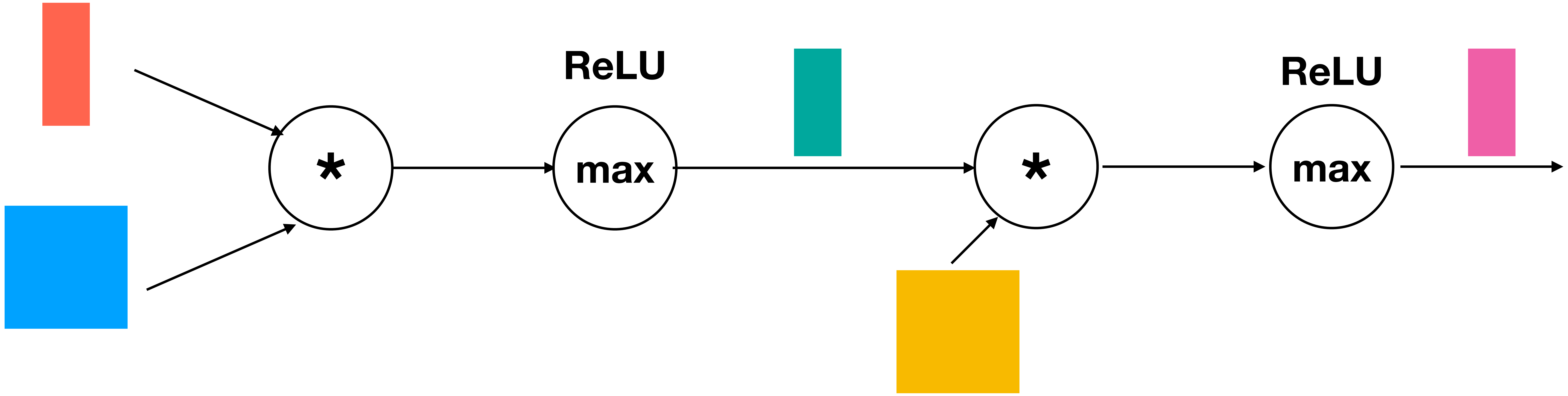
What can be a loss function ?



Two-layer model

Fully connected layers

Reference



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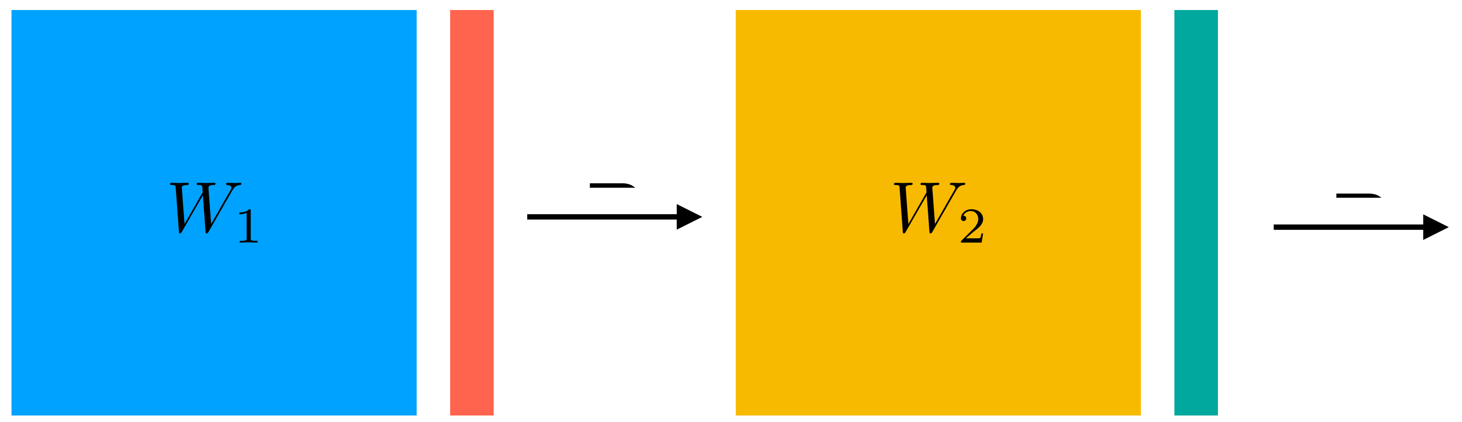
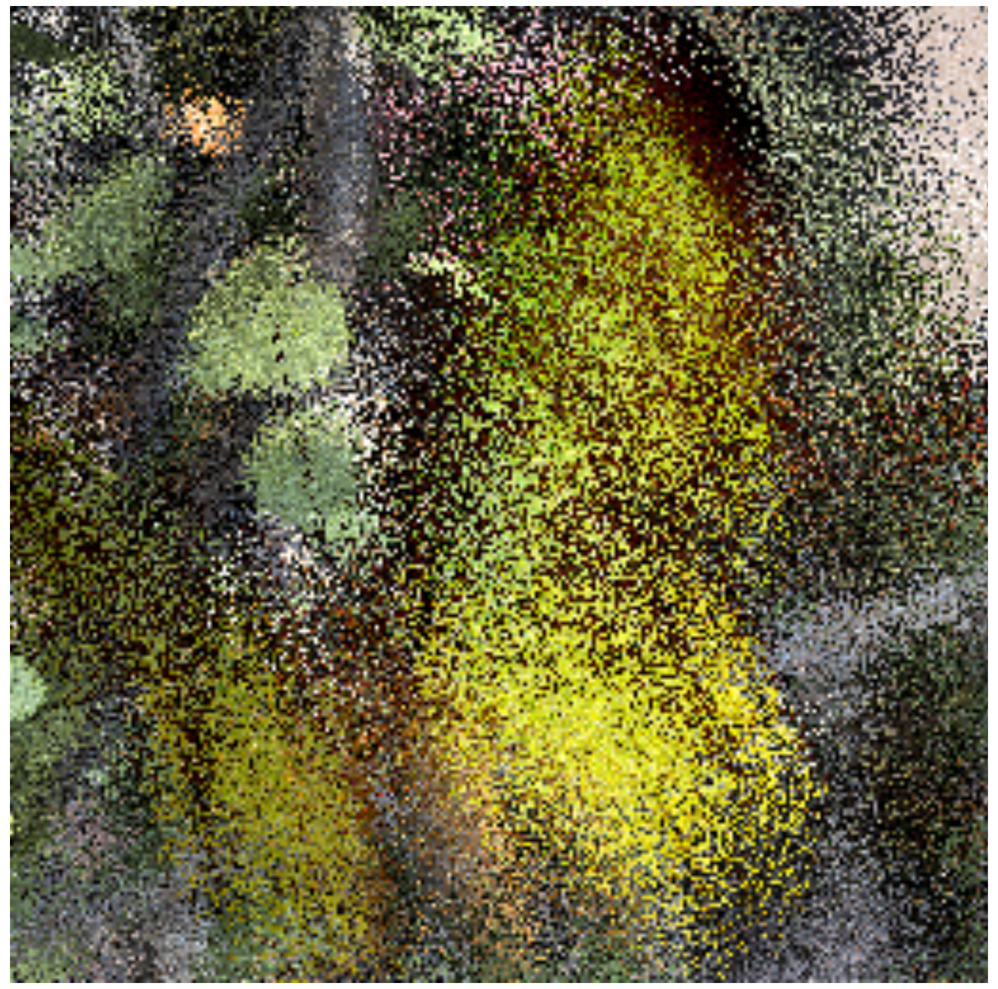


Two-layer model

Fully connected layers



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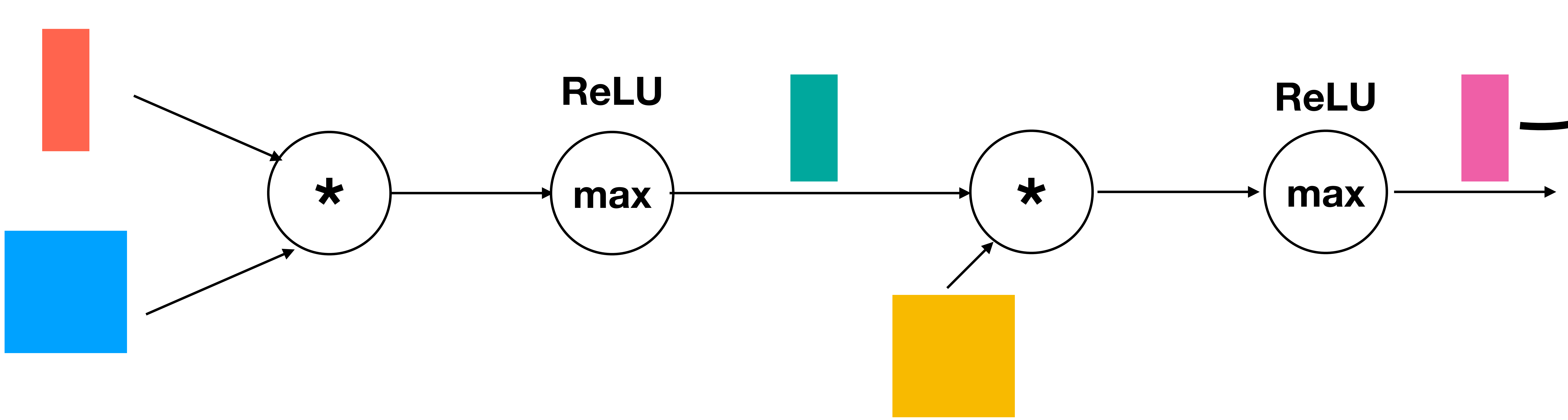

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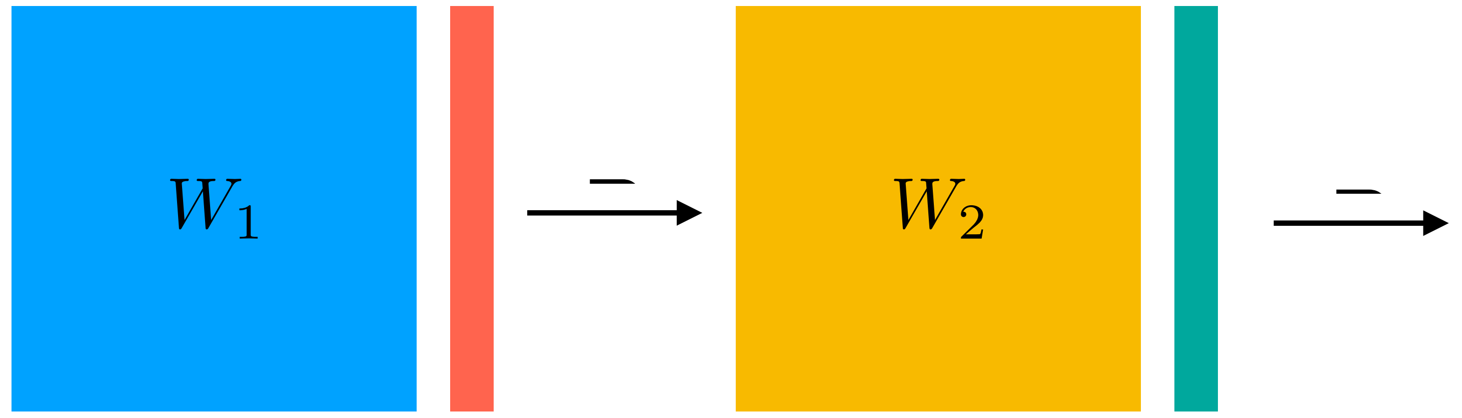
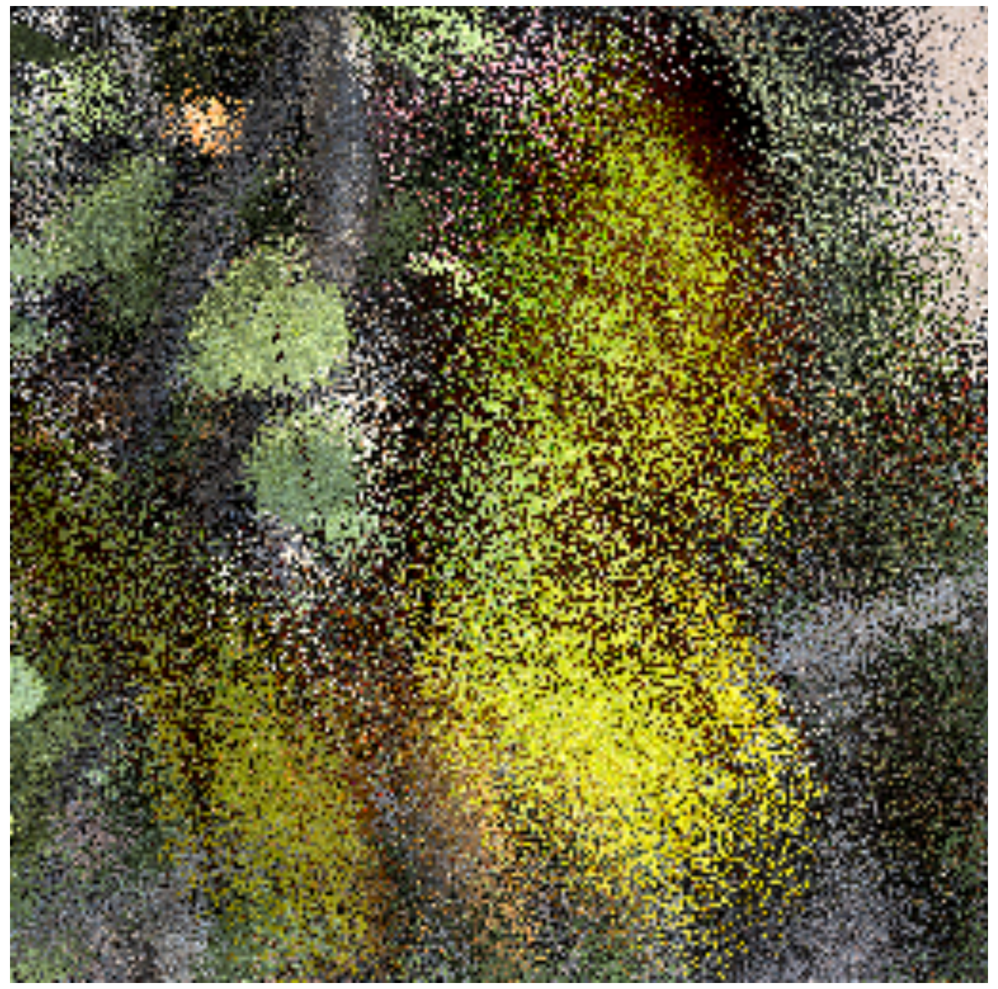
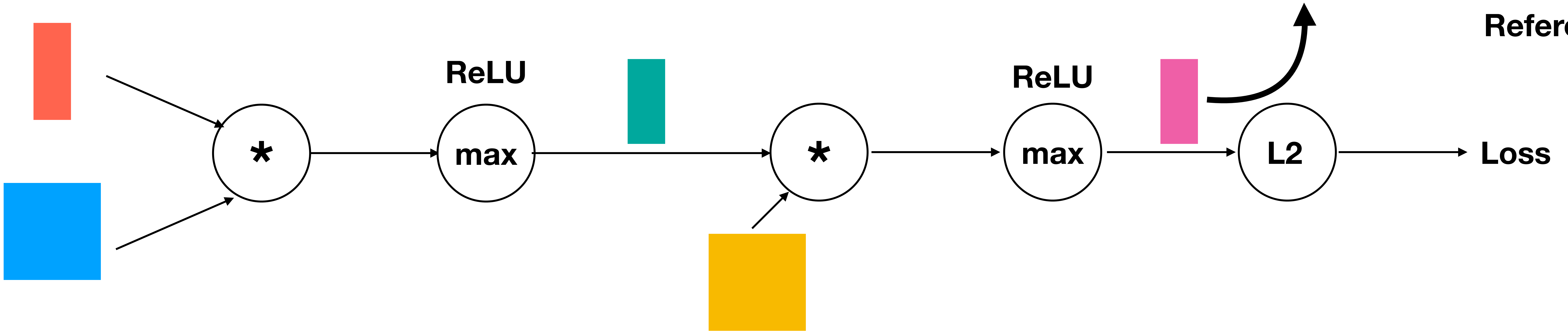


Two-layer model

Fully connected layers

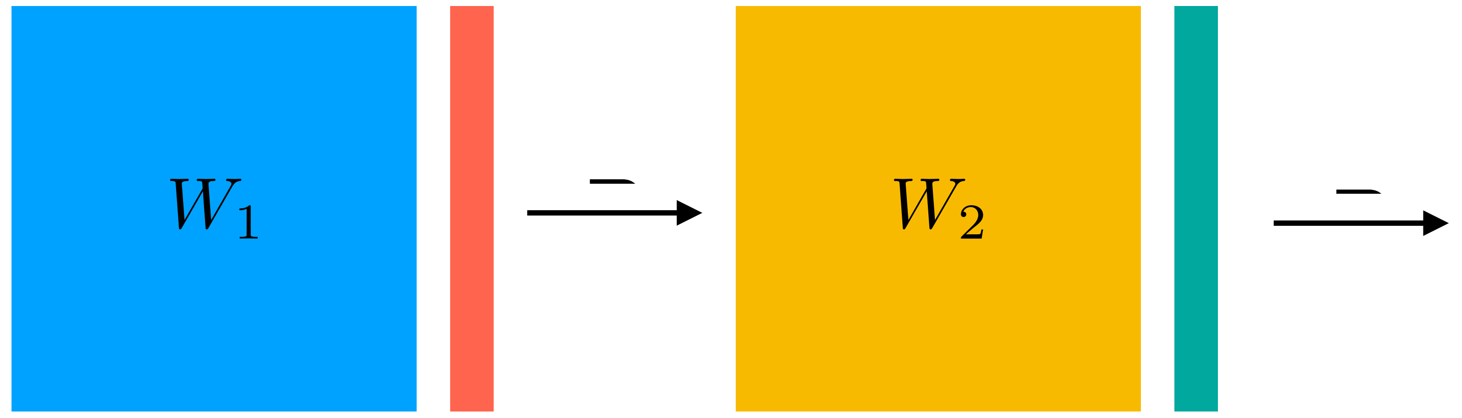


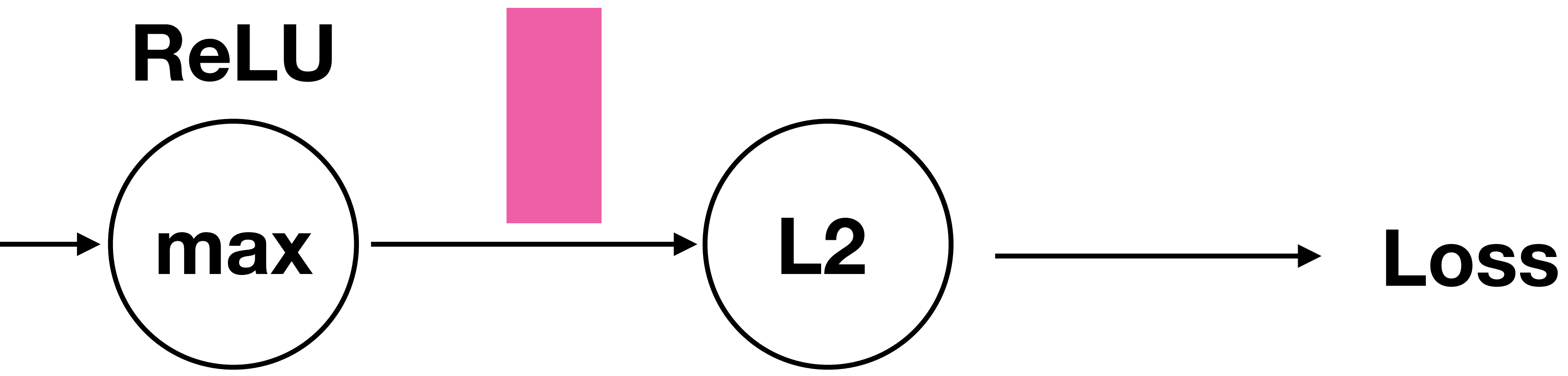
Reference



What can be a loss function ?

Two-layer model





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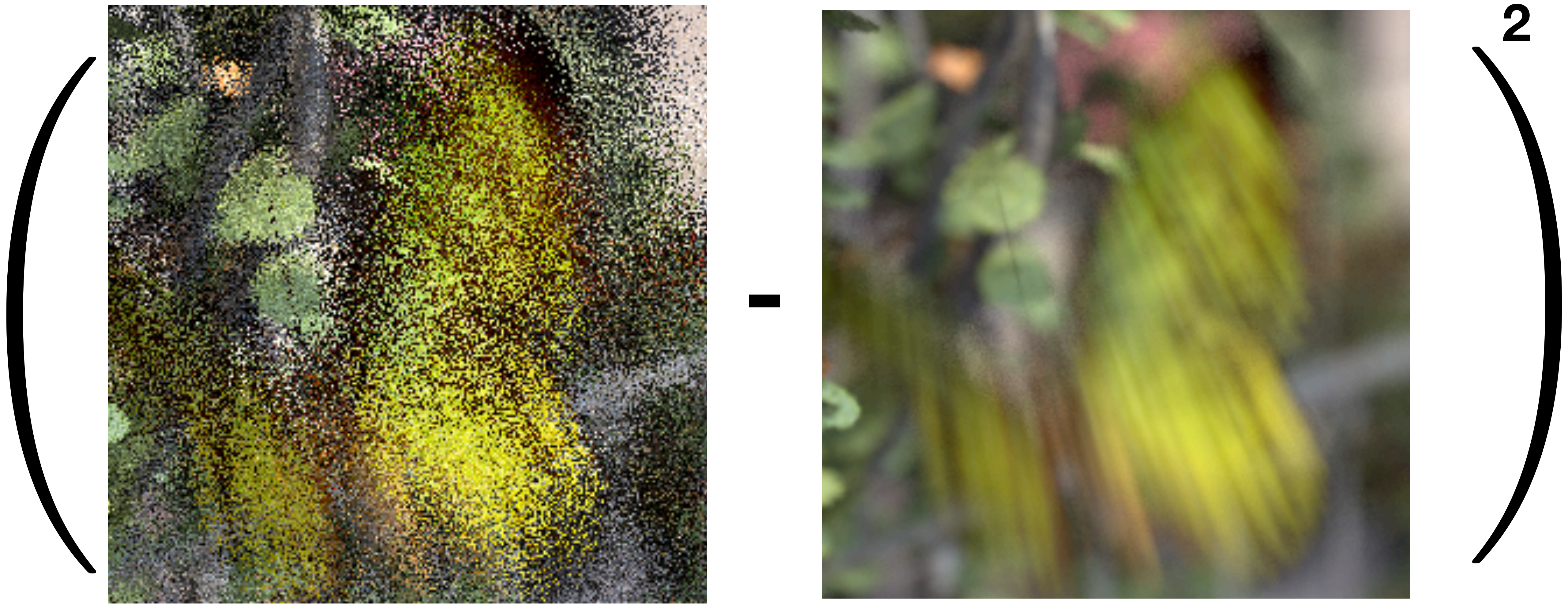
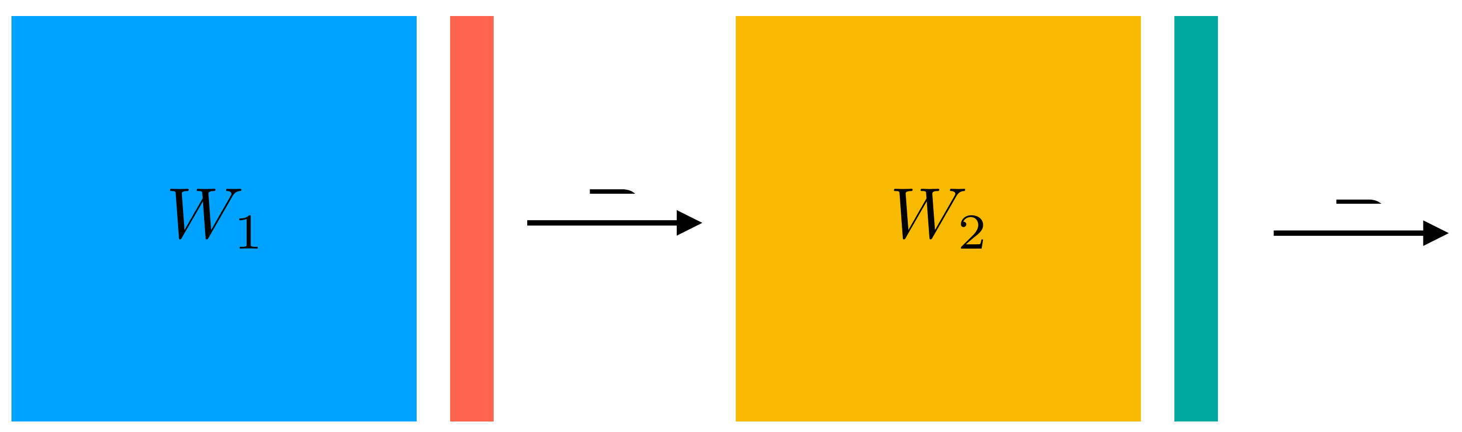
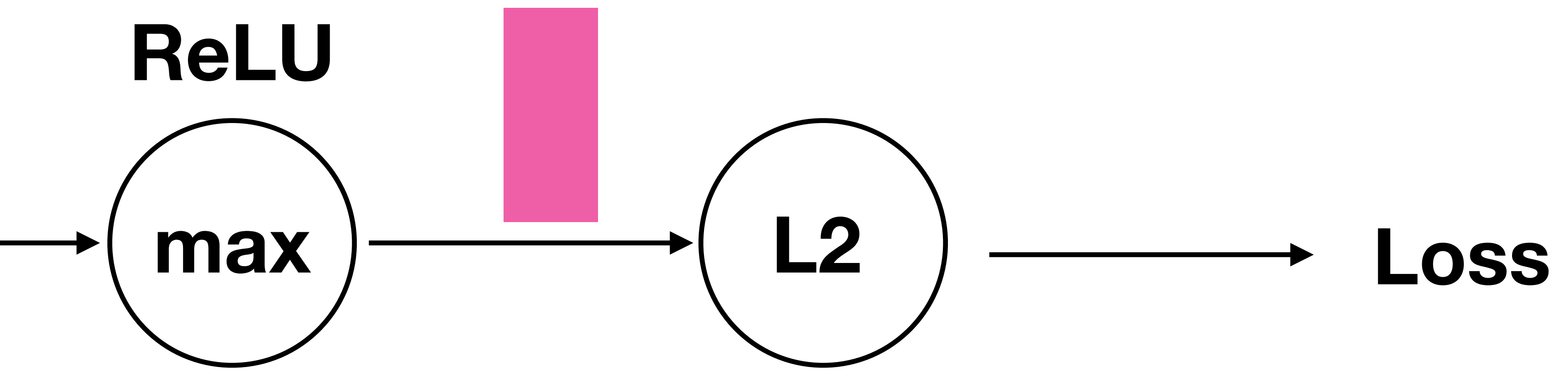
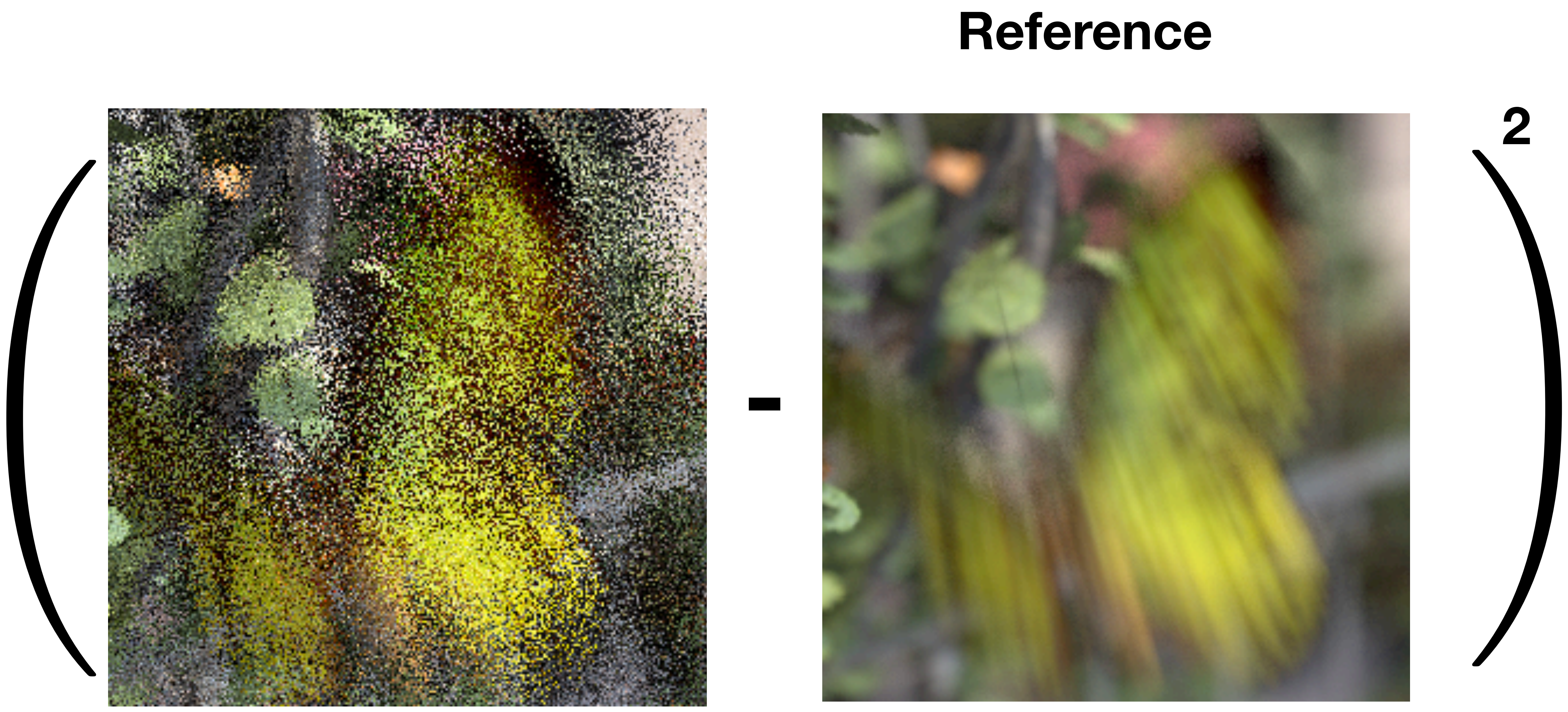


What can be a loss function ?

Two-layer model



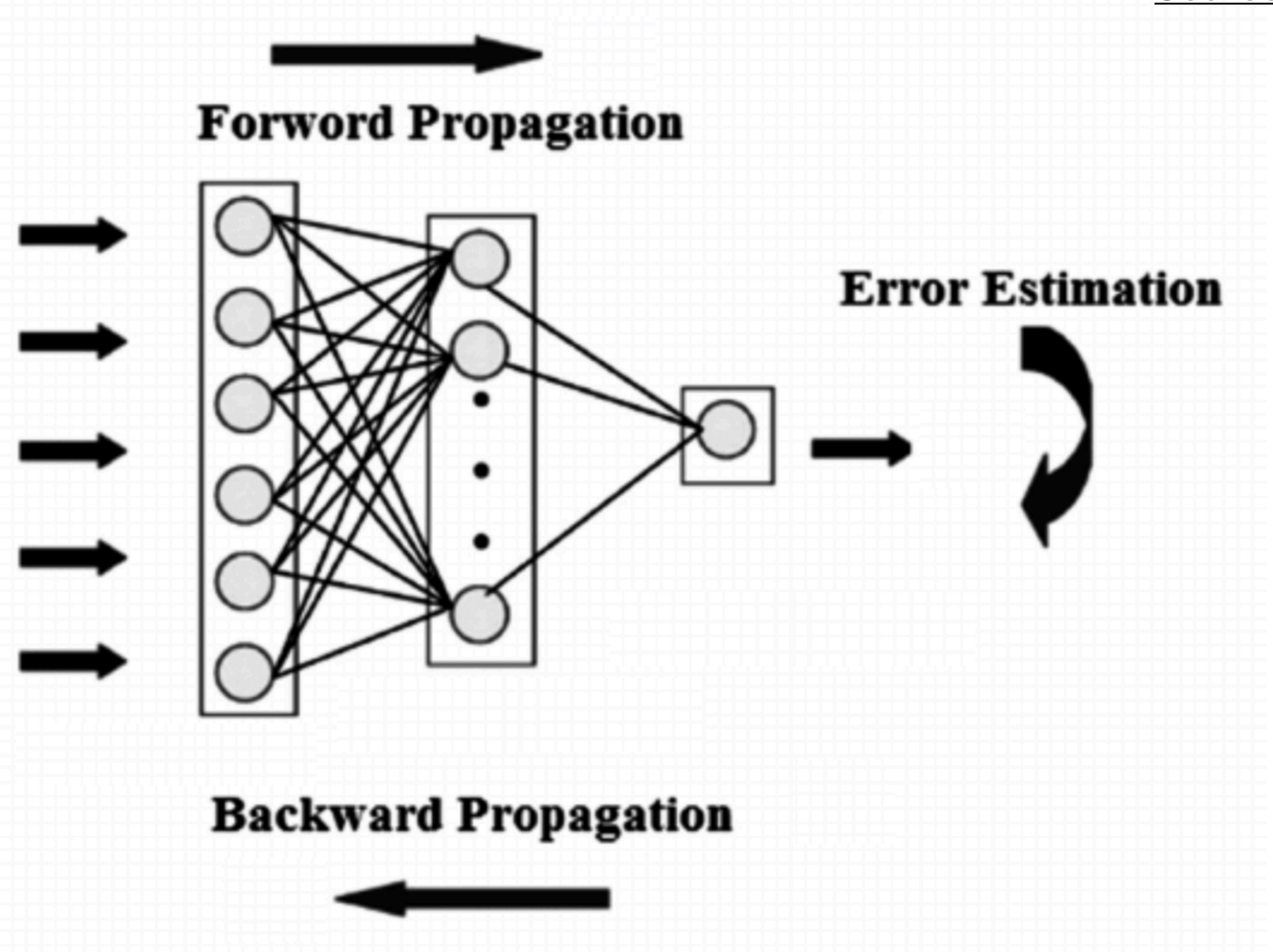




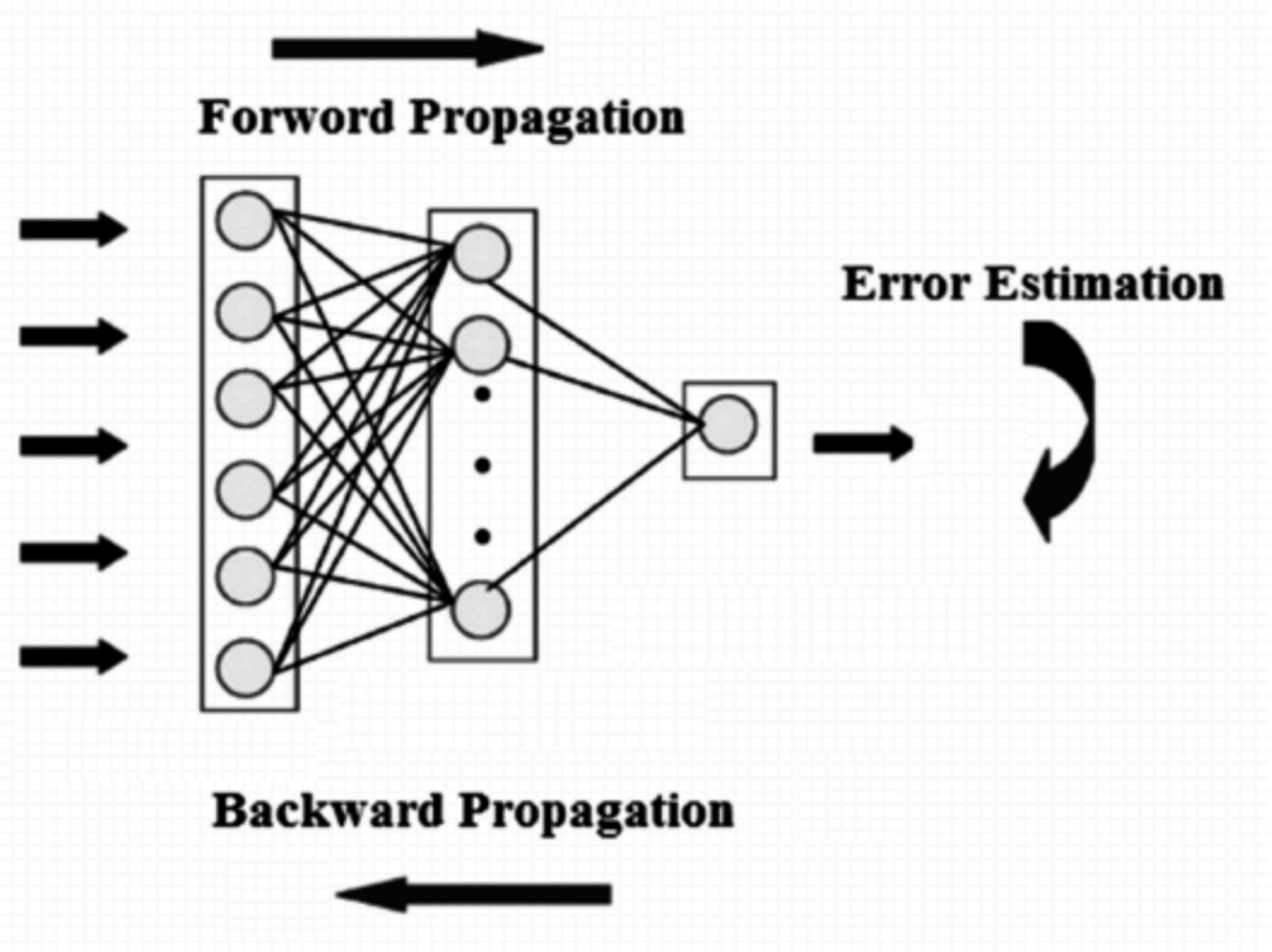
What can be a loss function ?

Two-layer model: Back propagation

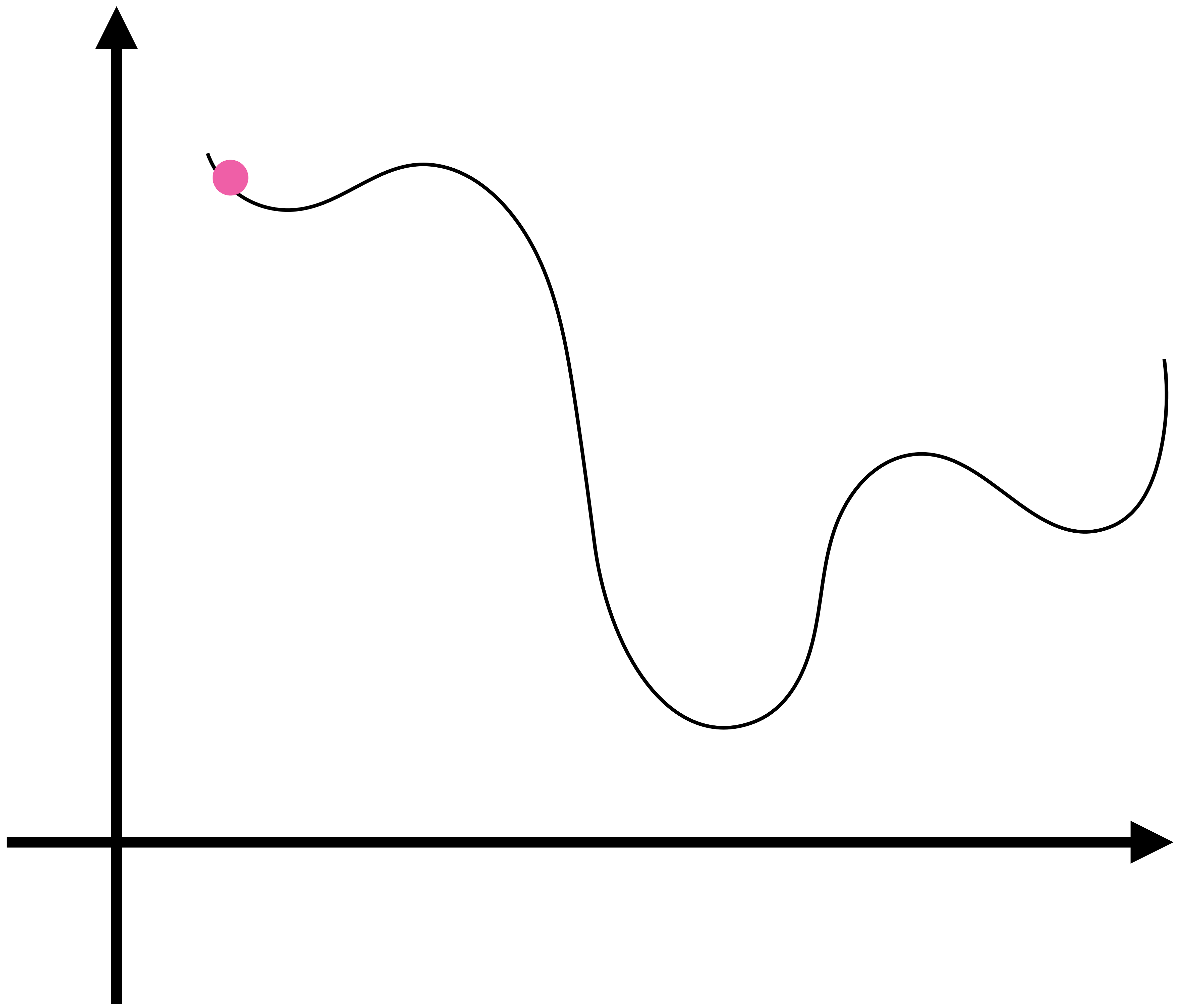
Source link



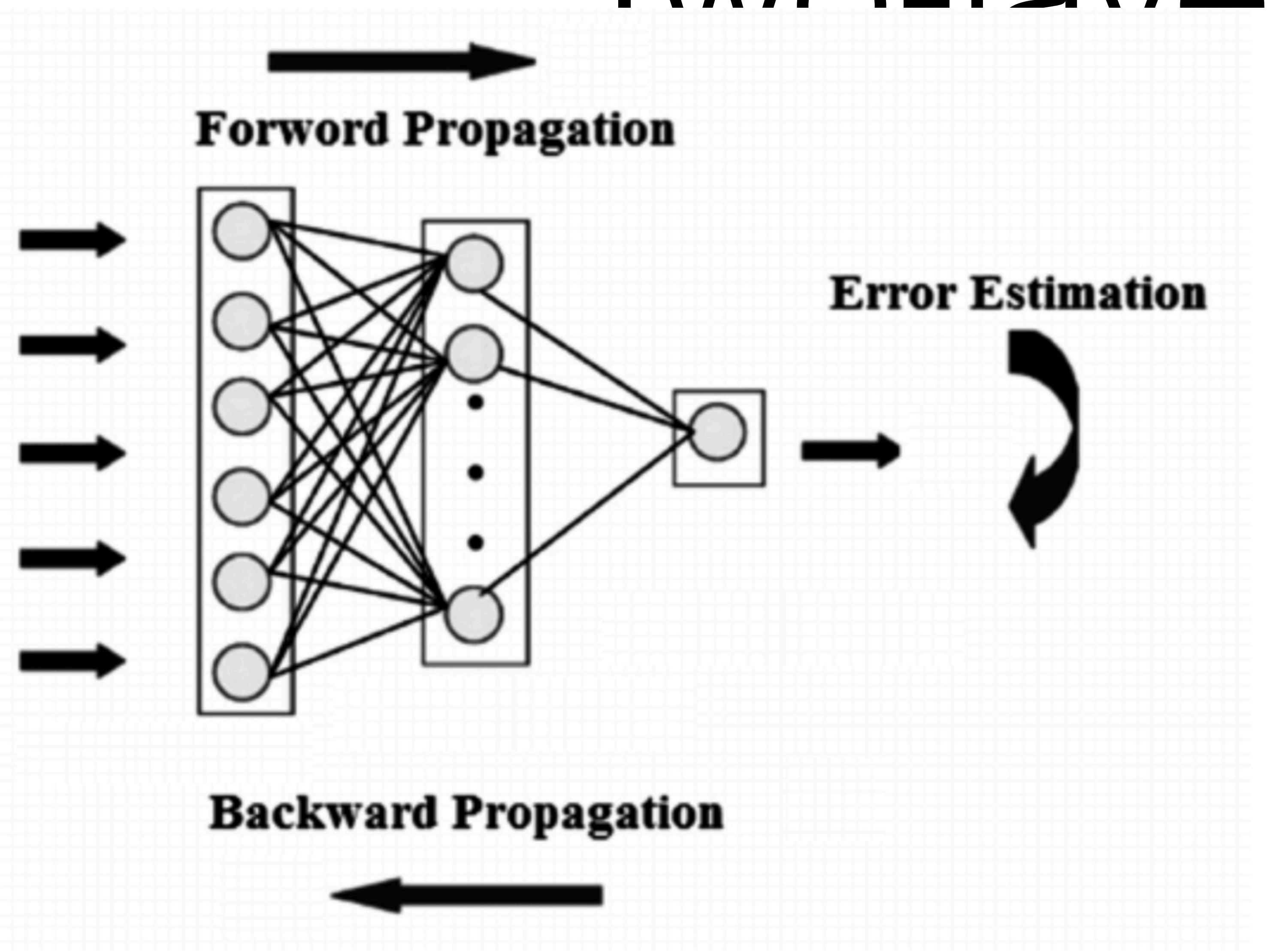
Two-layer model: Back propagation



Gradient Descent Algorithm
for back propagation



Two-layer model: Back propagation



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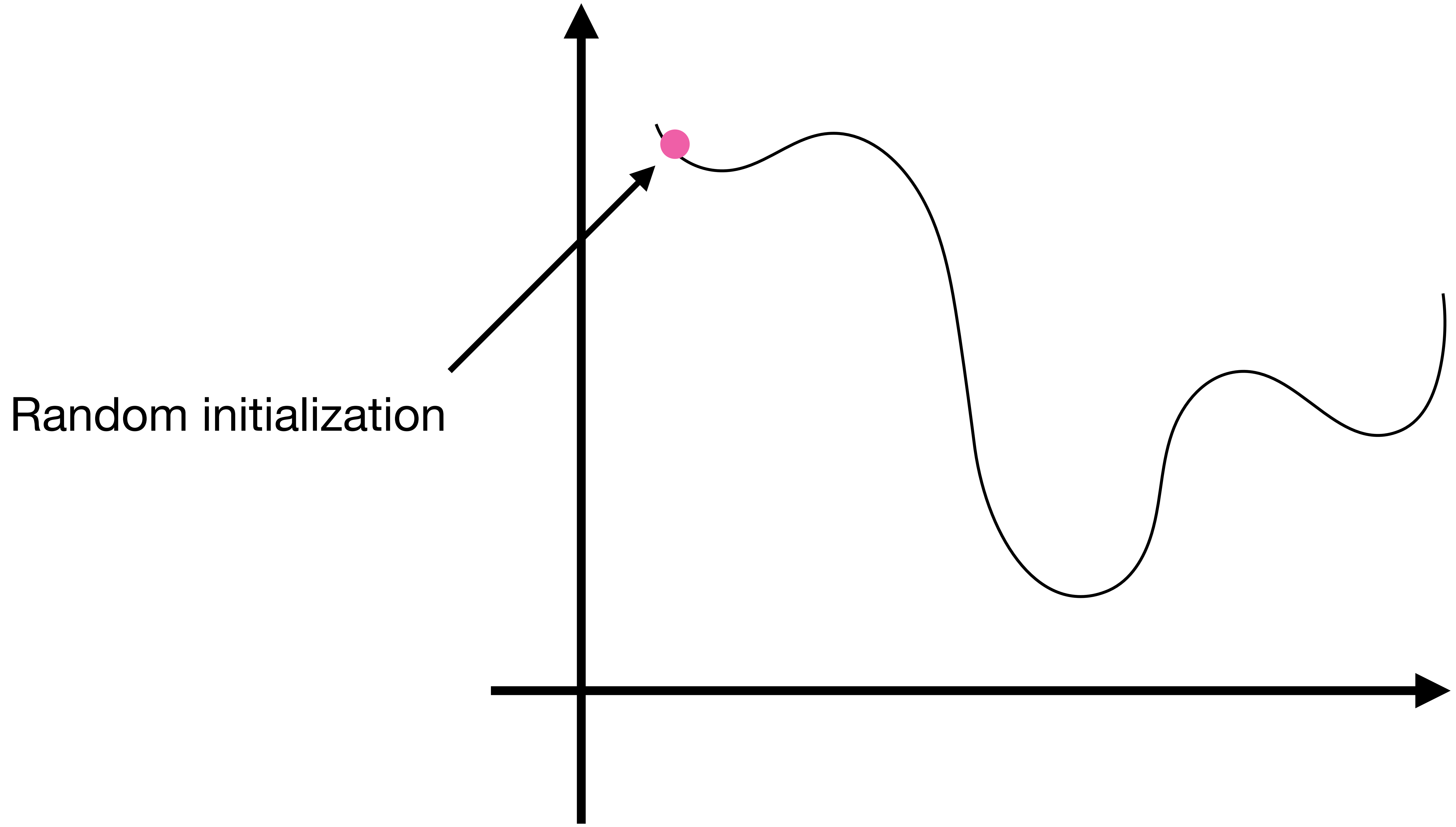
for back propagation



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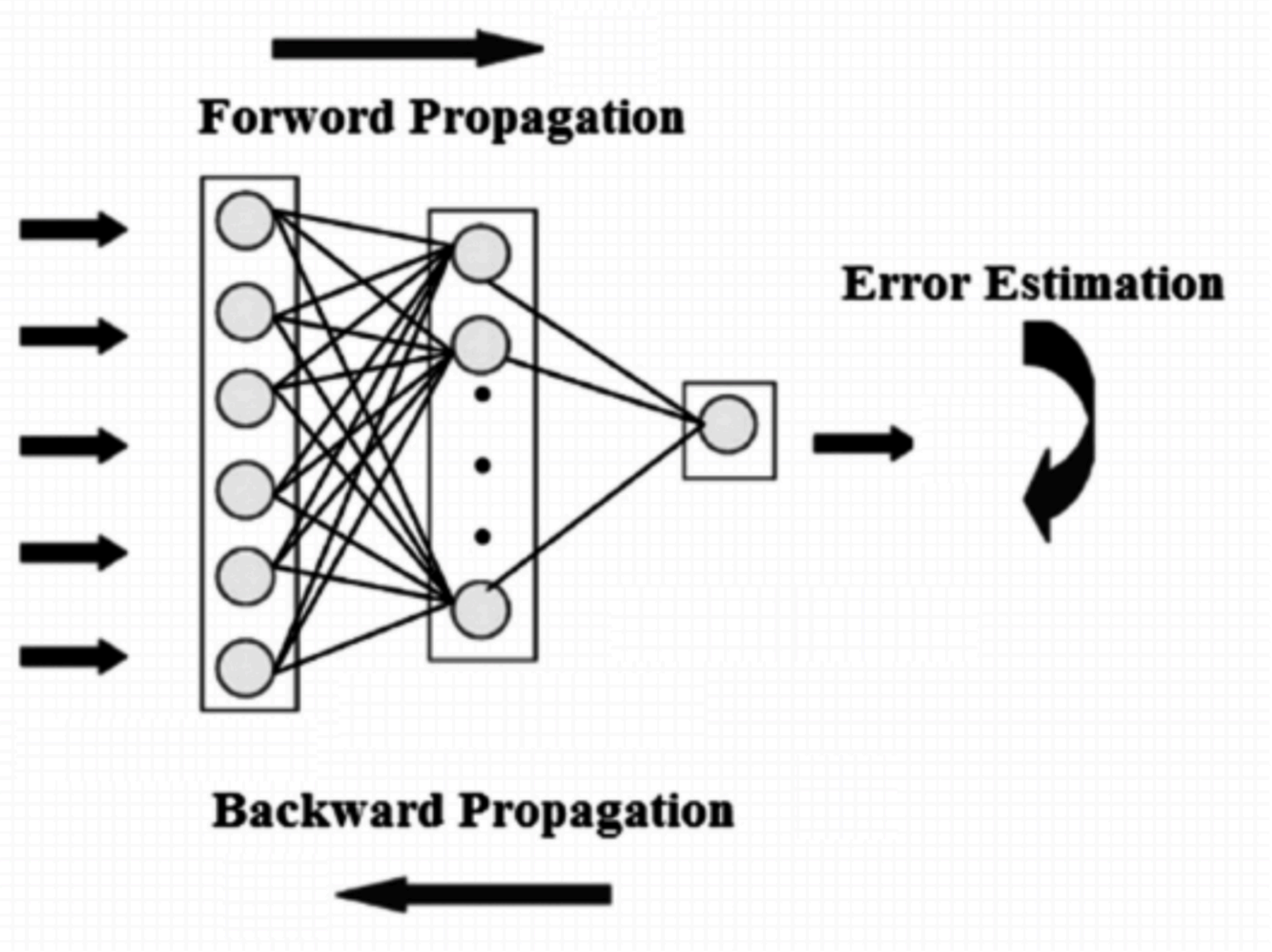

Gradient Descent Algorithm
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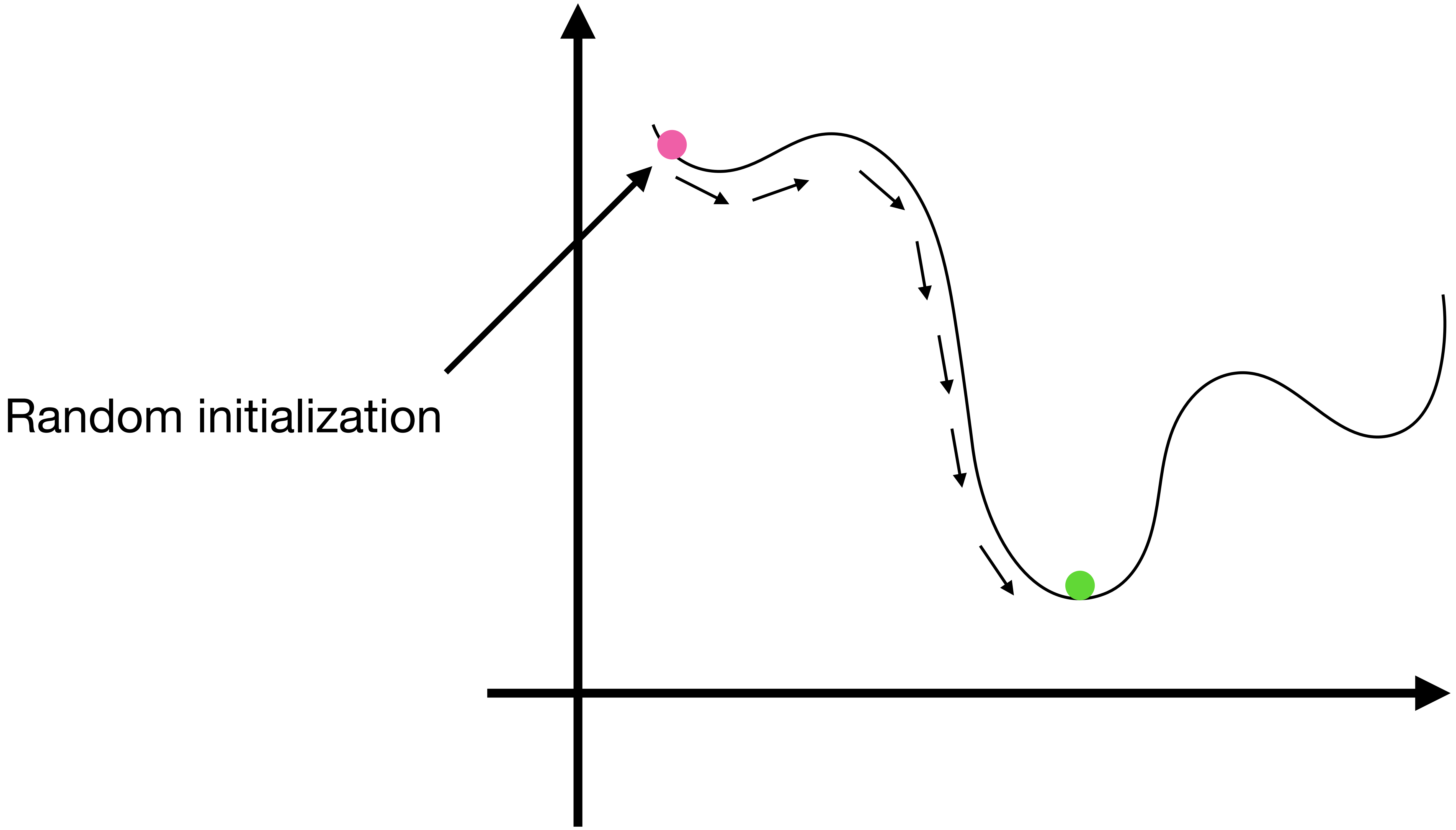
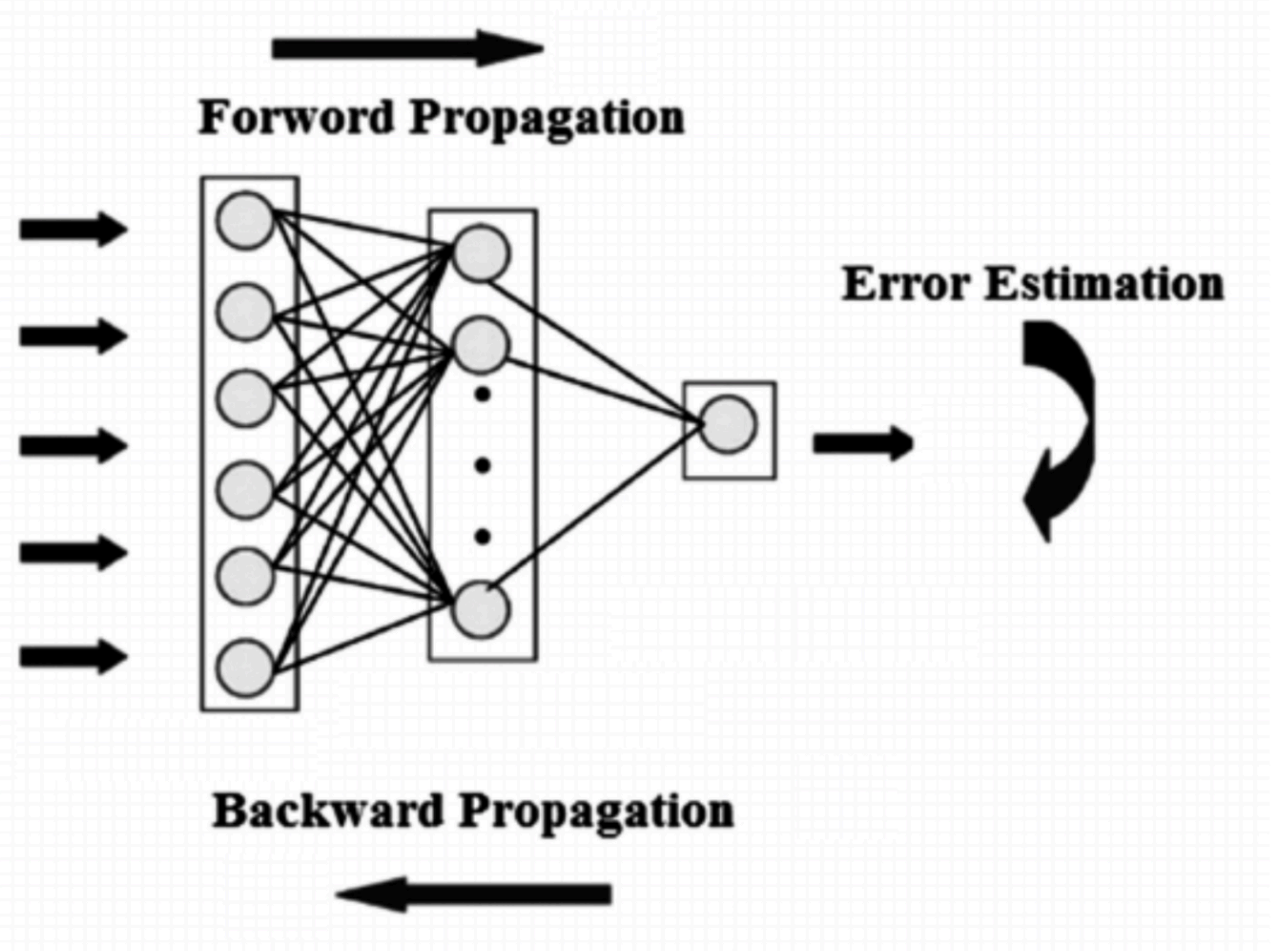
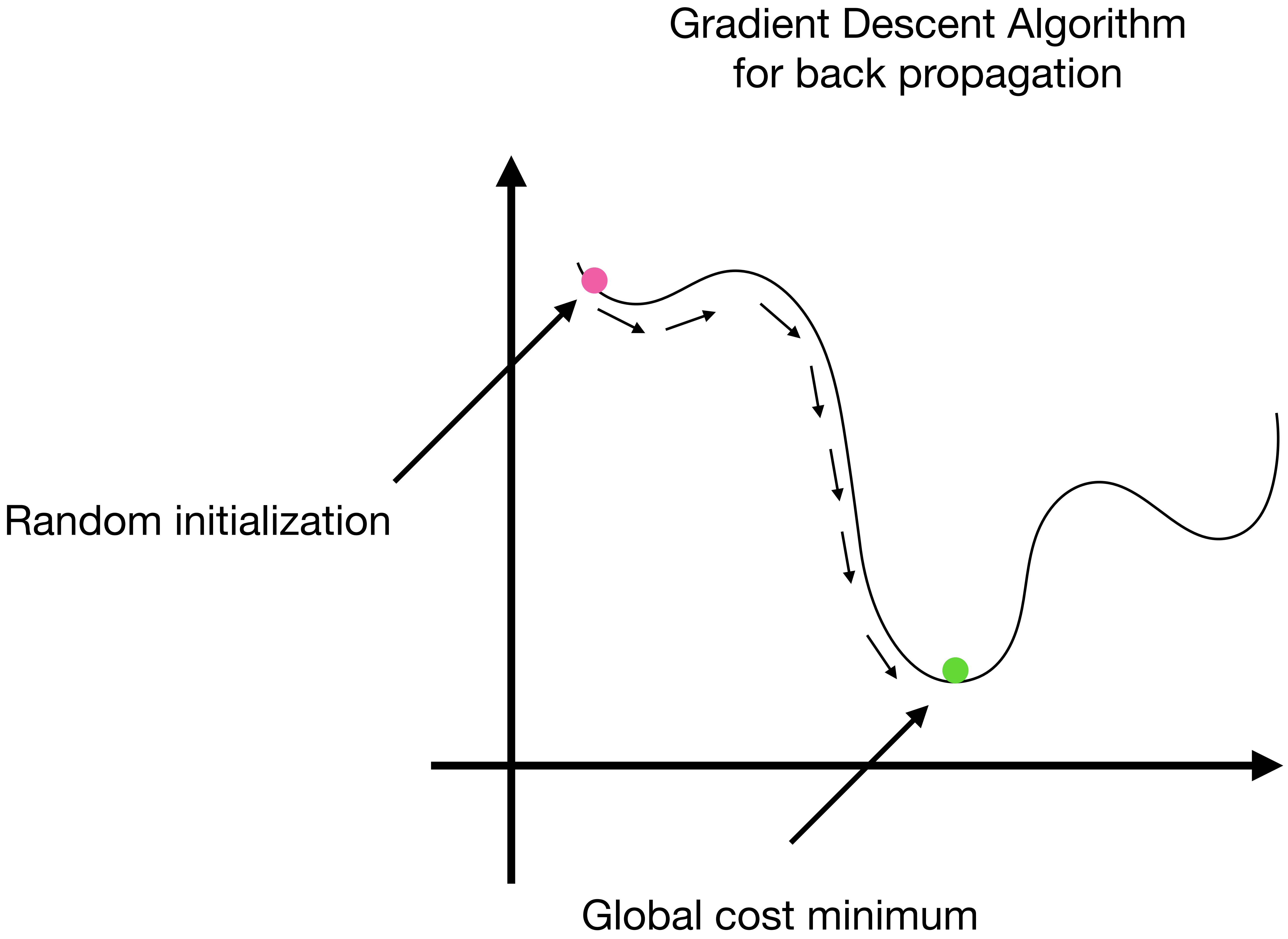
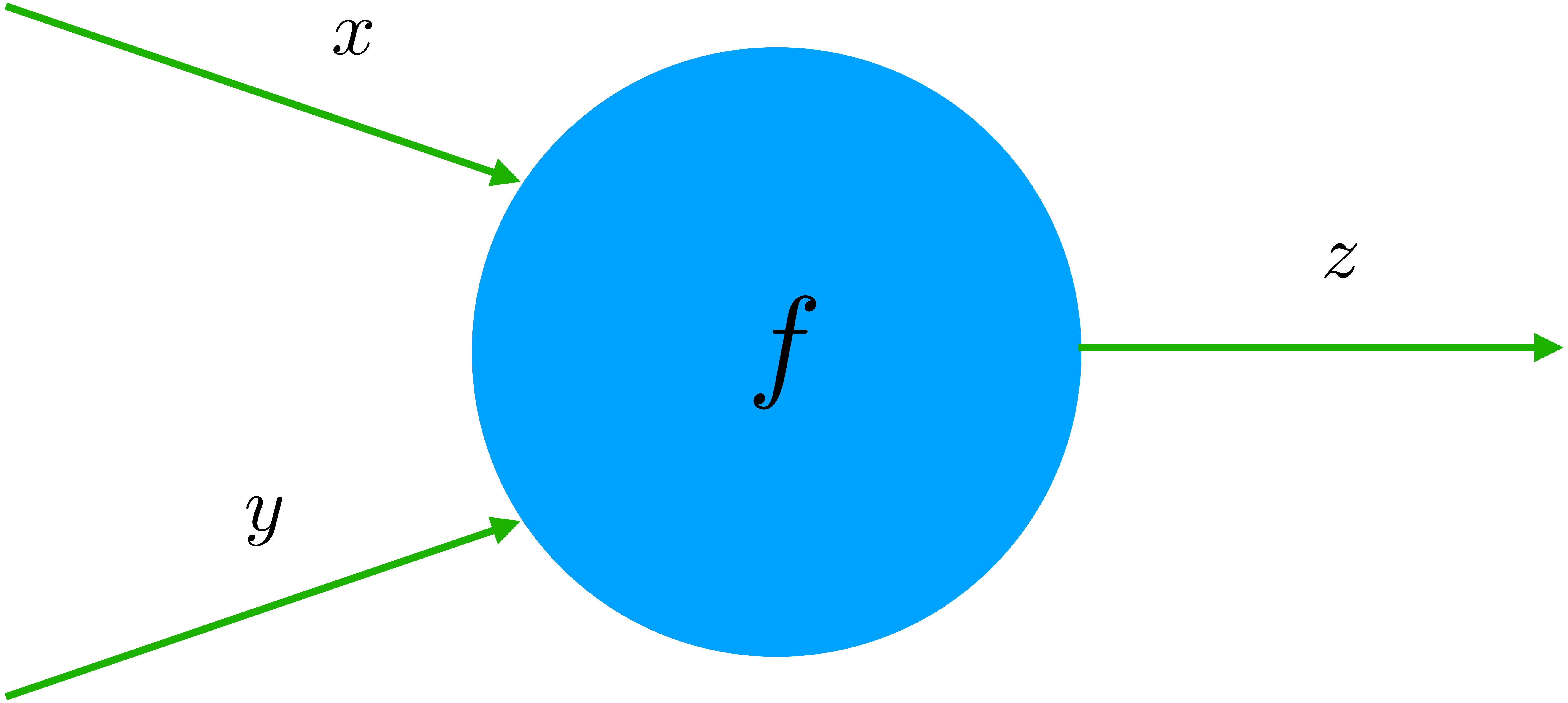


Two-layer model: Back propagation





Back Propagation



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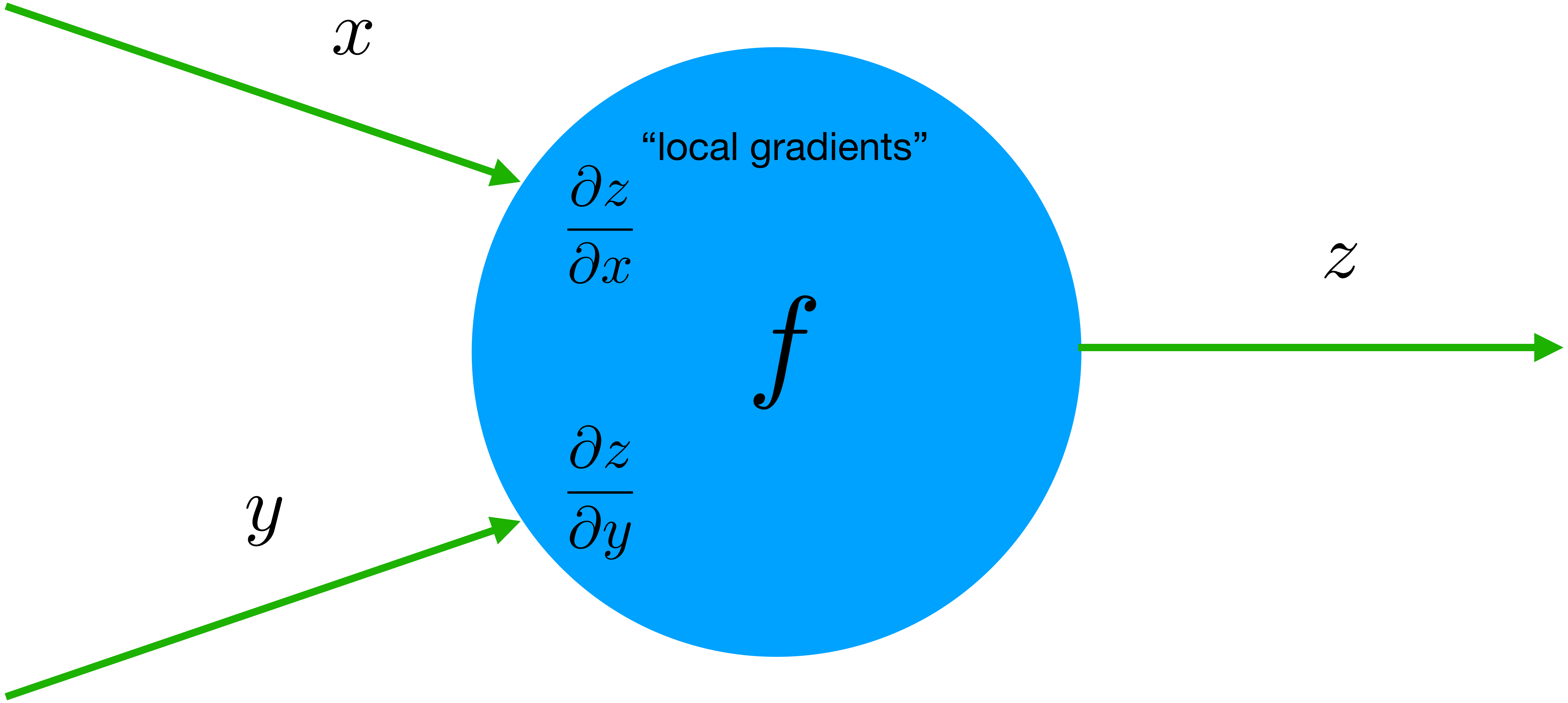
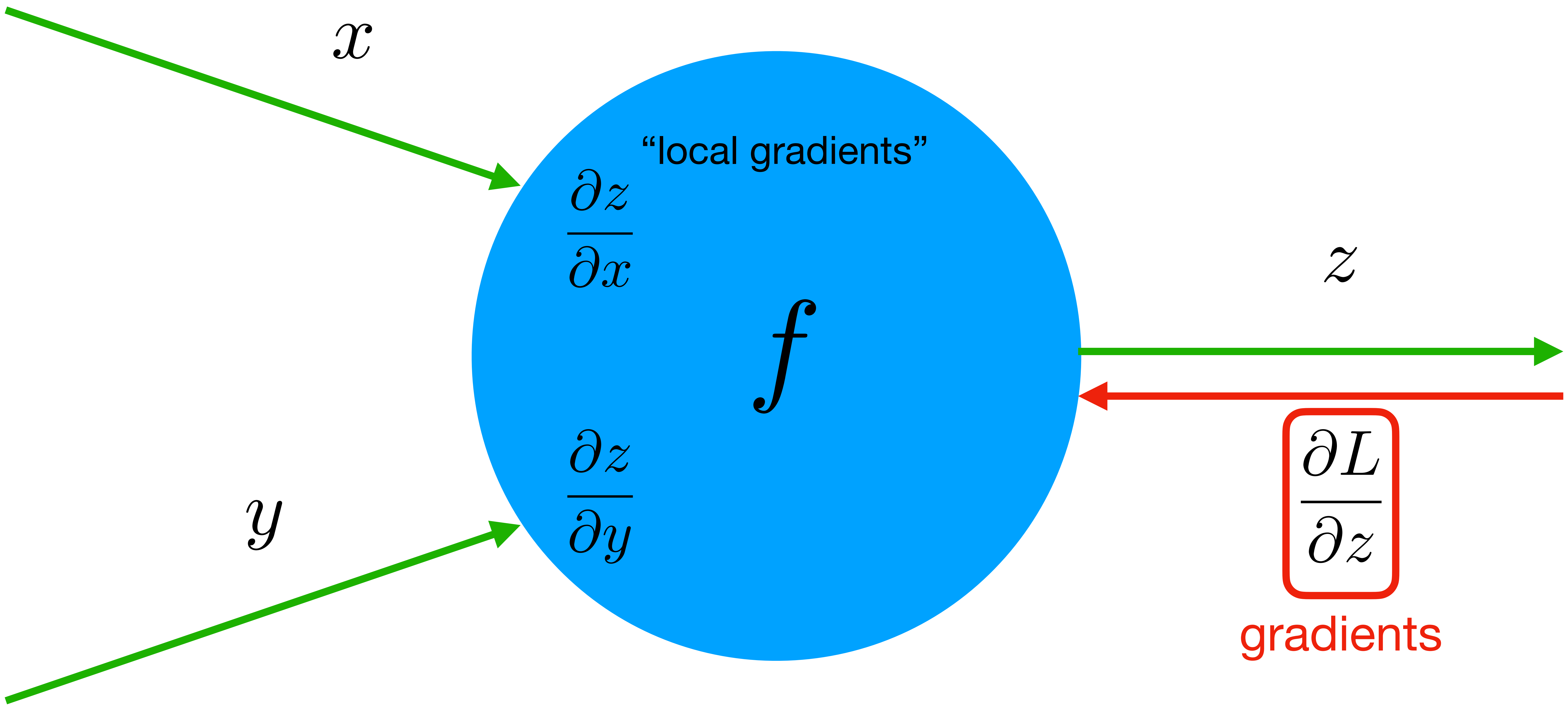
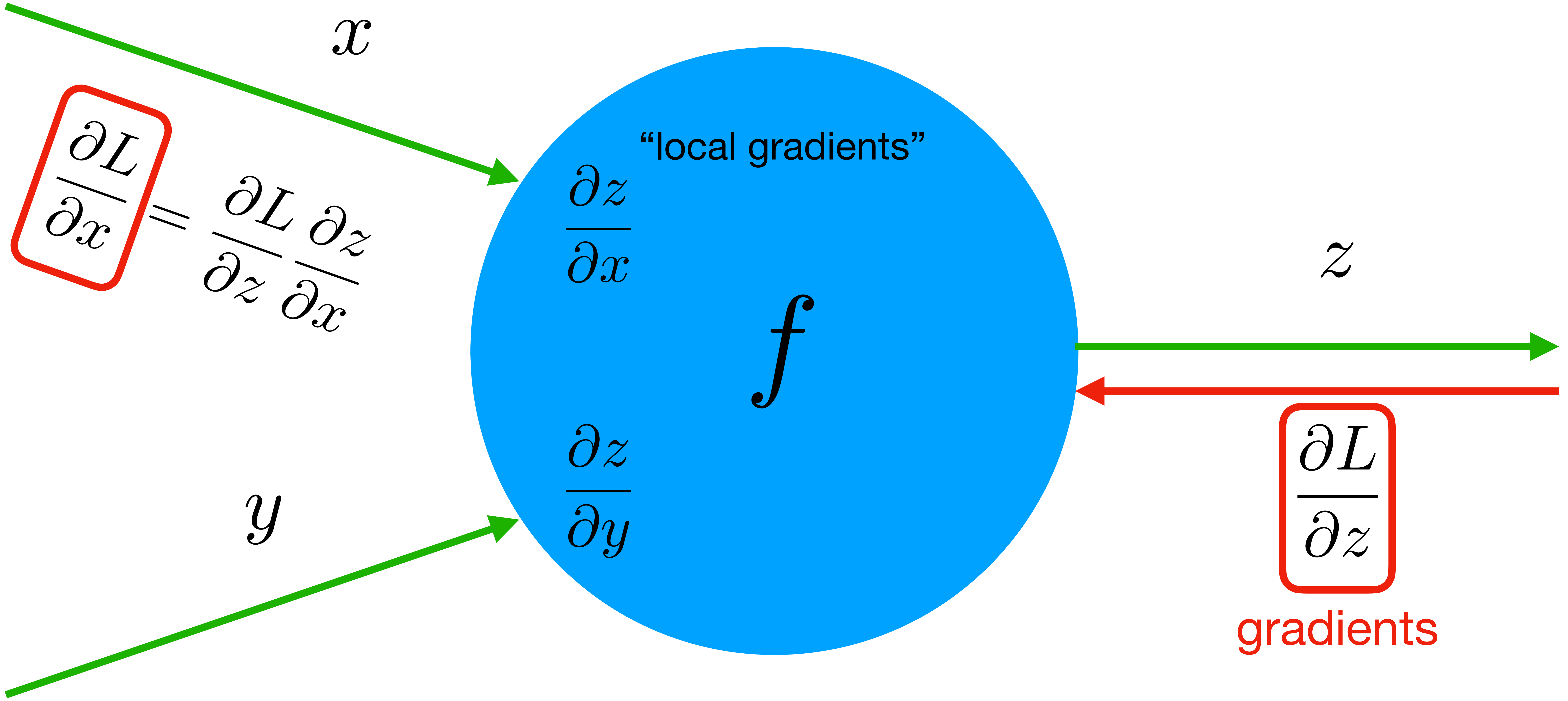
Back Propagation



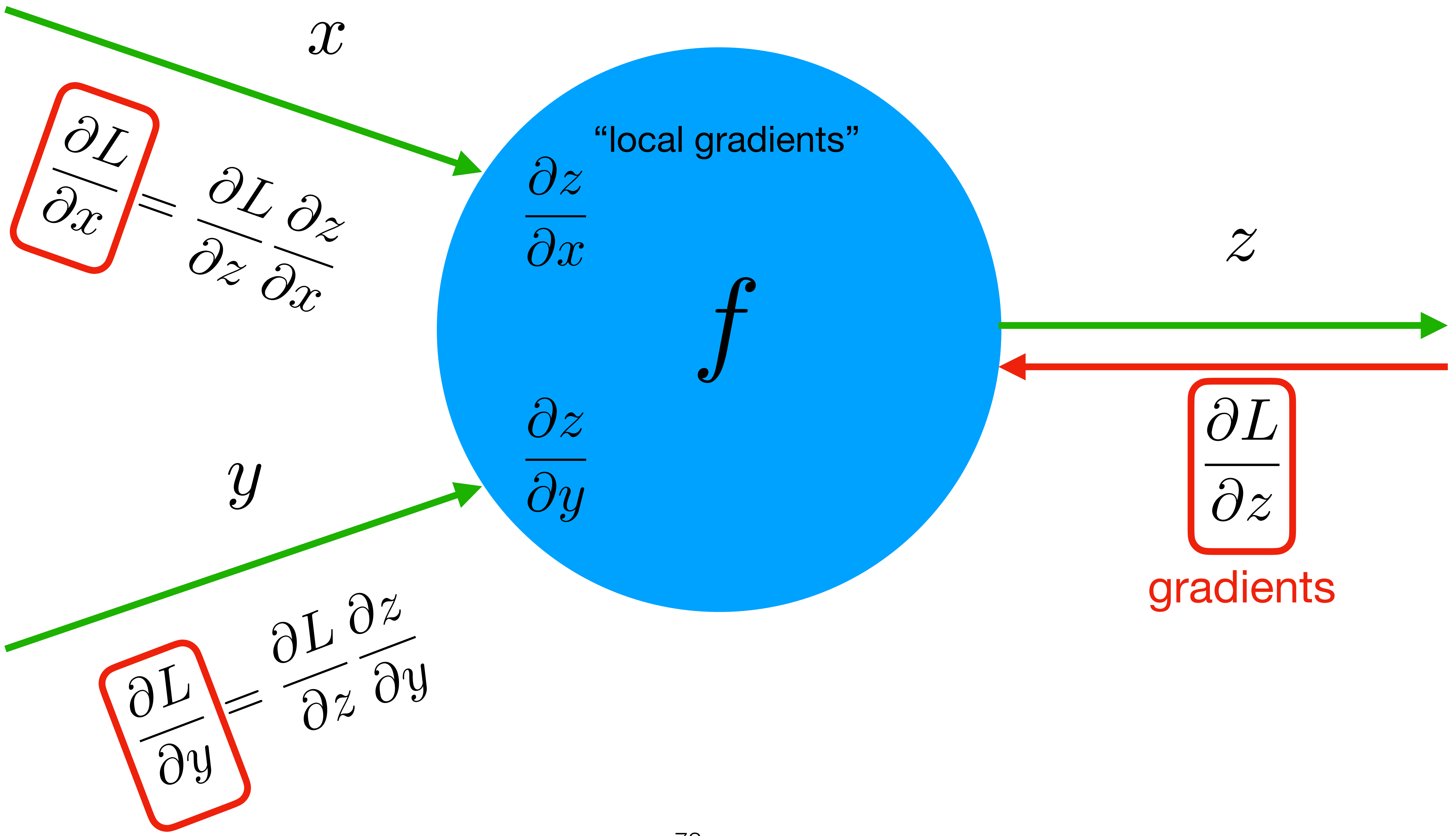
Back Propagation



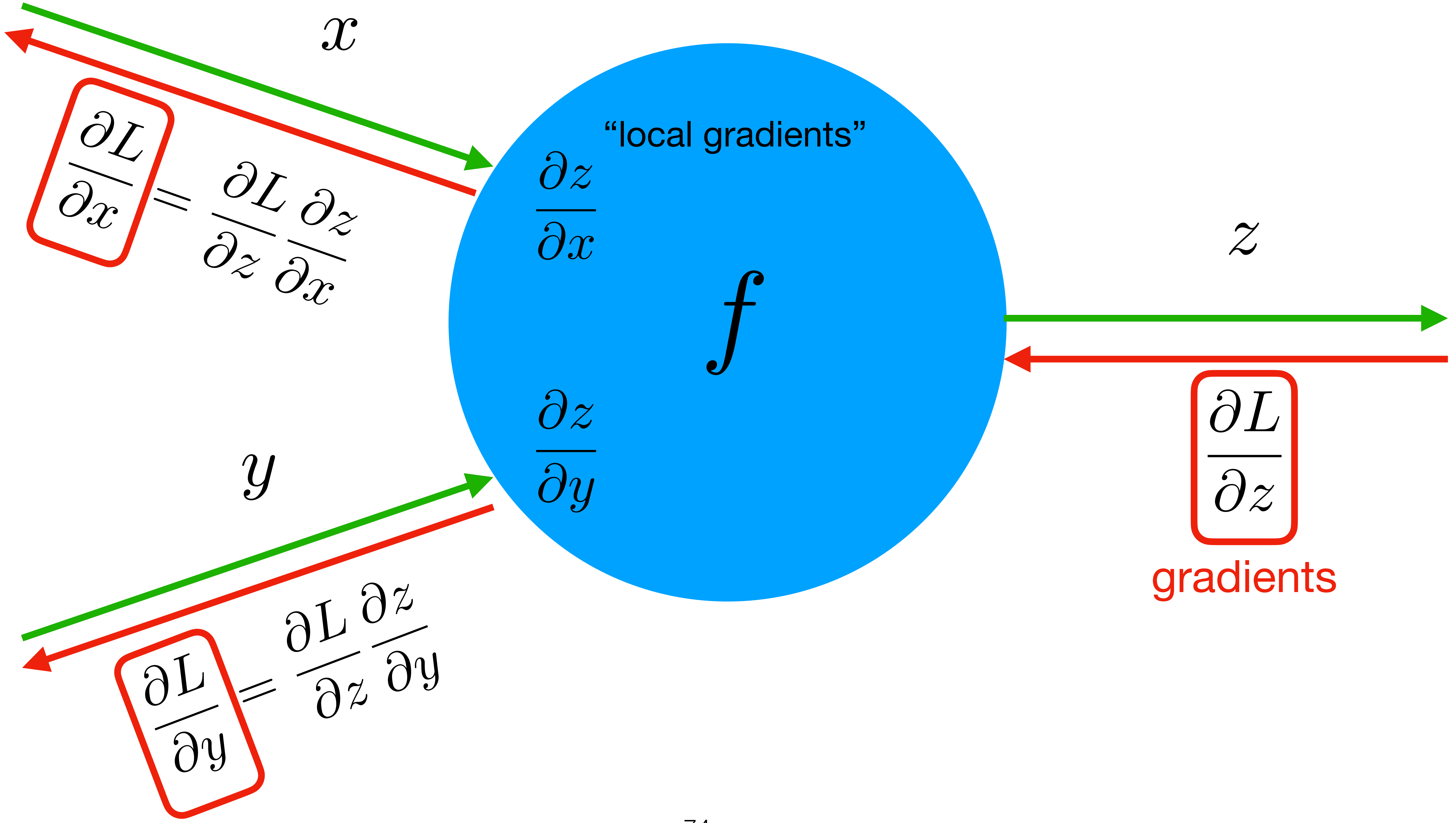
Back Propagation



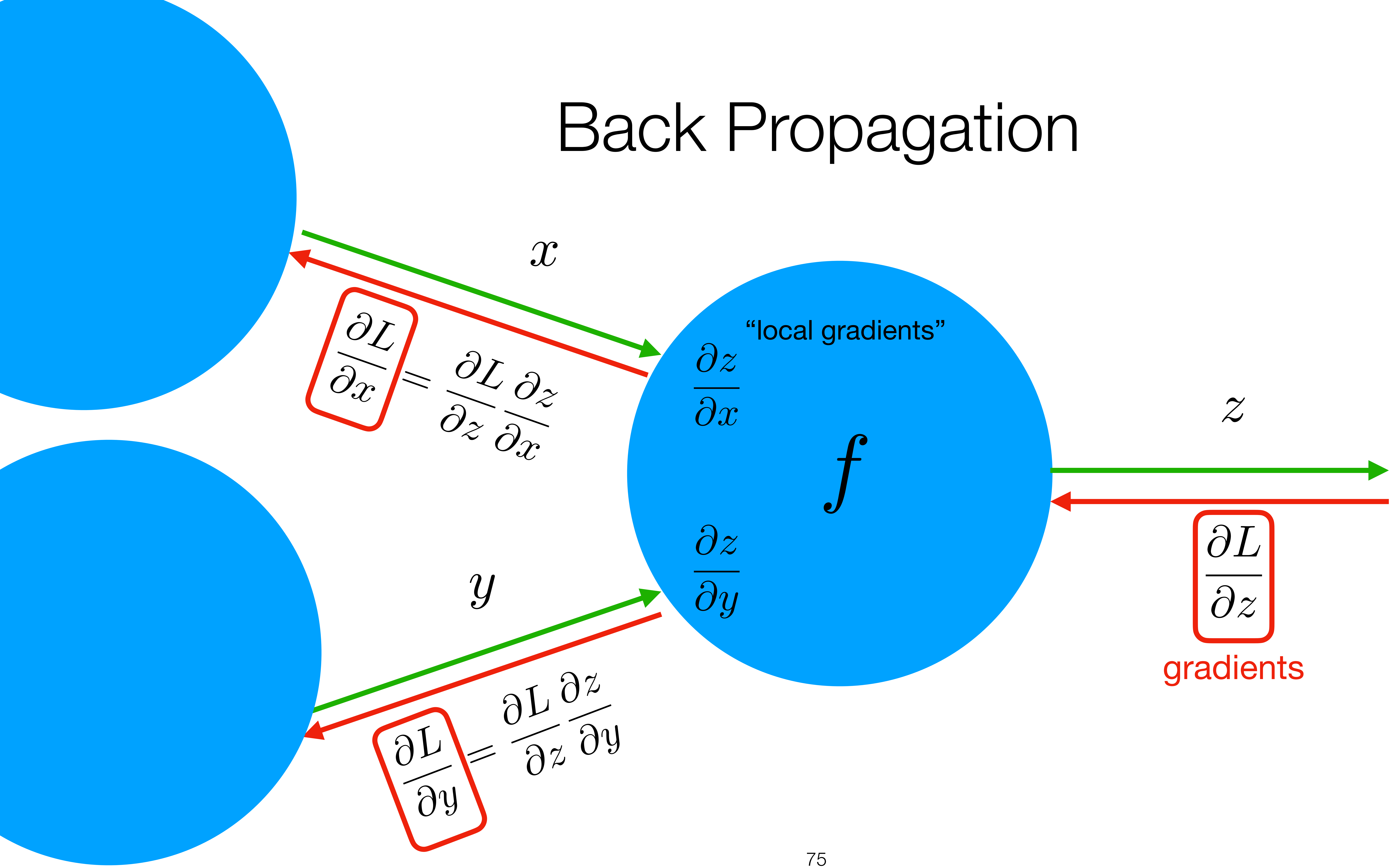
Back Propagation



Back Propagation



Back Propagation

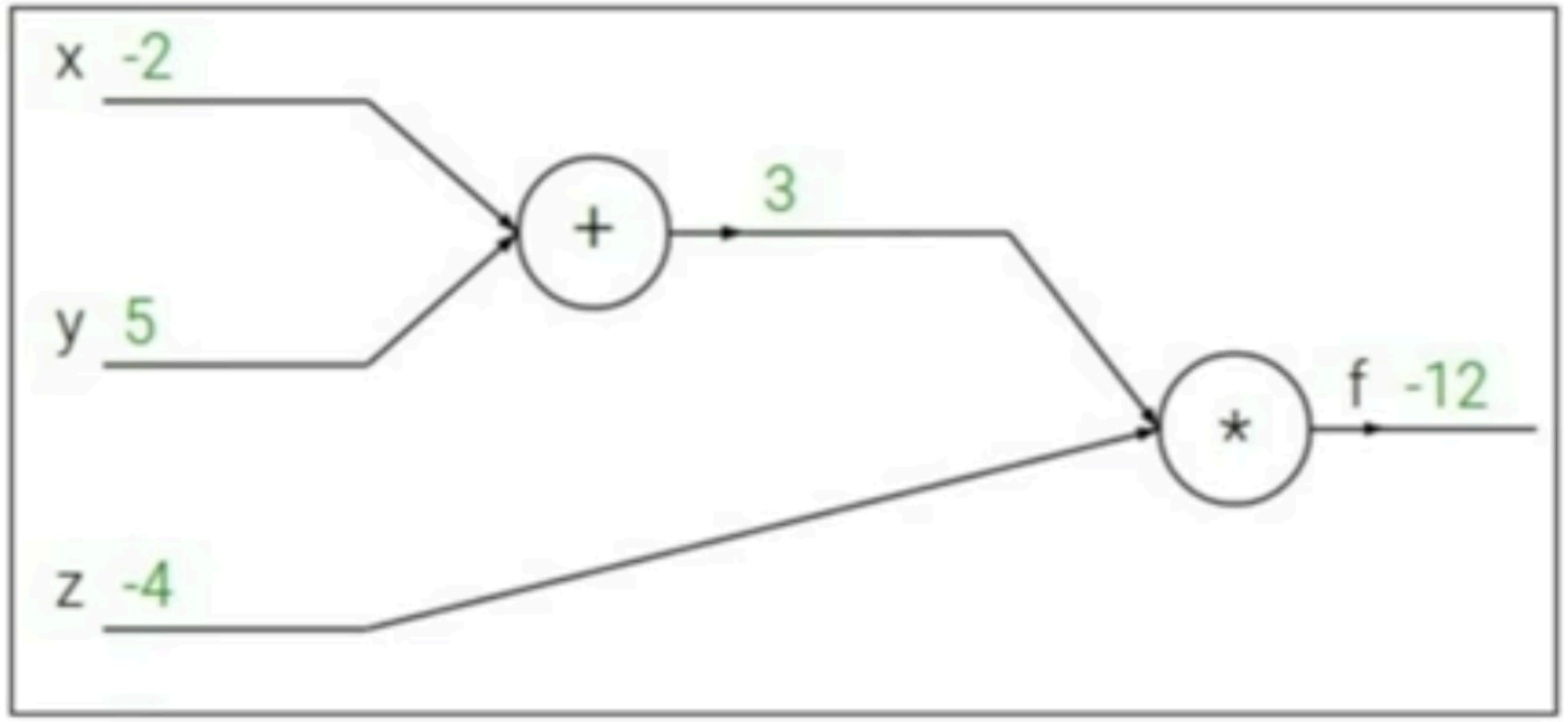


Back Propagation

Backpropagation: a simple example

$$f(x, y, z) = (x + y)z$$

e.g. x = -2, y = 5, z = -4



Slides courtesy: Stanford Online Course

Back Propagation

Backpropagation: a simple example

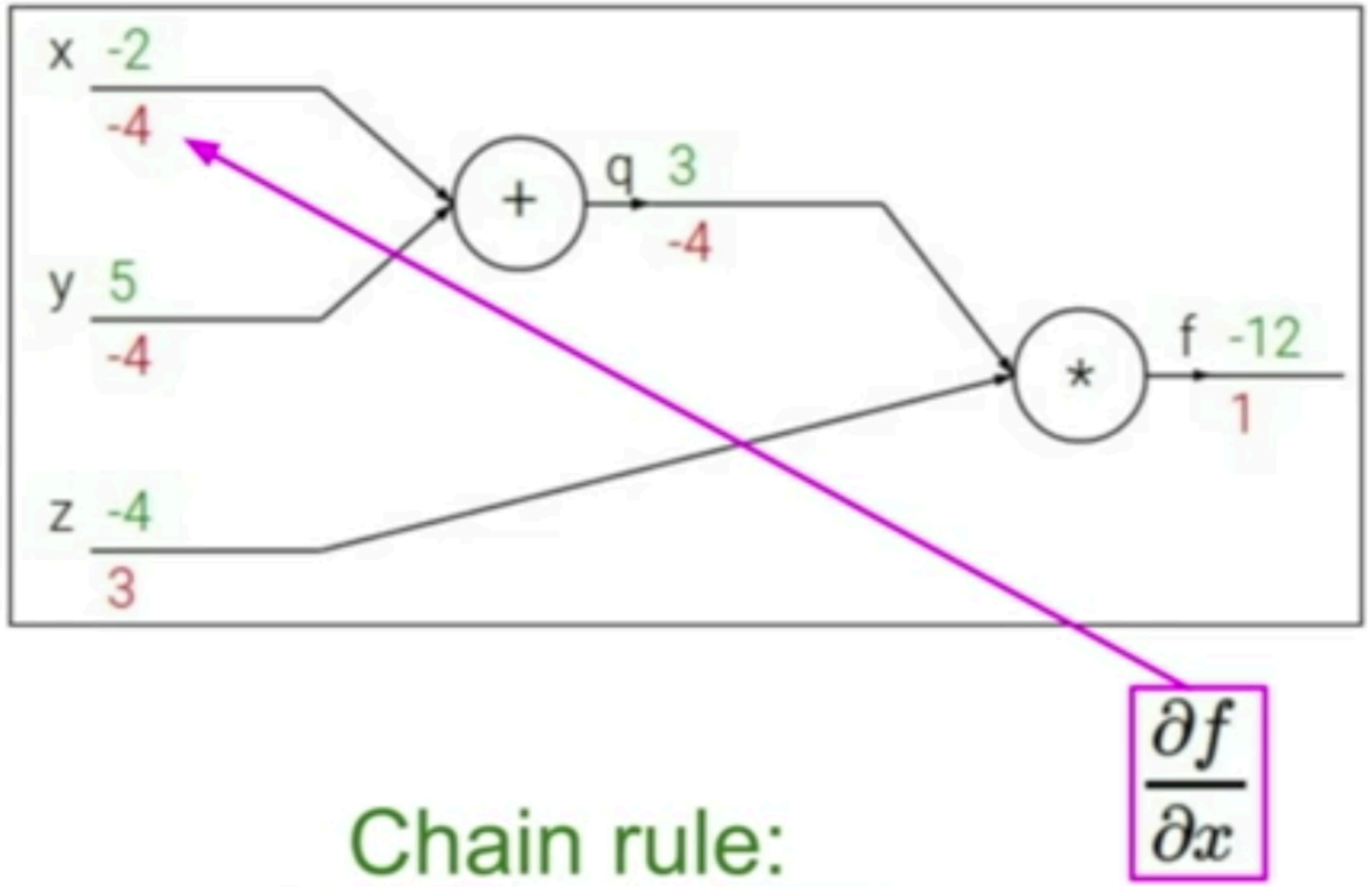
$$f(x,y,z) = (x+y)z$$

e.g. x = -2, y = 5, z = -4

$$q = x + y \qquad \frac{\partial q}{\partial x} = 1, \frac{\partial q}{\partial y} = 1$$

$$f = qz \qquad \frac{\partial f}{\partial q} = z, \frac{\partial f}{\partial z} = q$$

Want: $\frac{\partial f}{\partial x}, \frac{\partial f}{\partial y}, \frac{\partial f}{\partial z}$



Chain rule:

$$\frac{\partial f}{\partial x} = \frac{\partial f}{\partial q} \frac{\partial q}{\partial x}$$

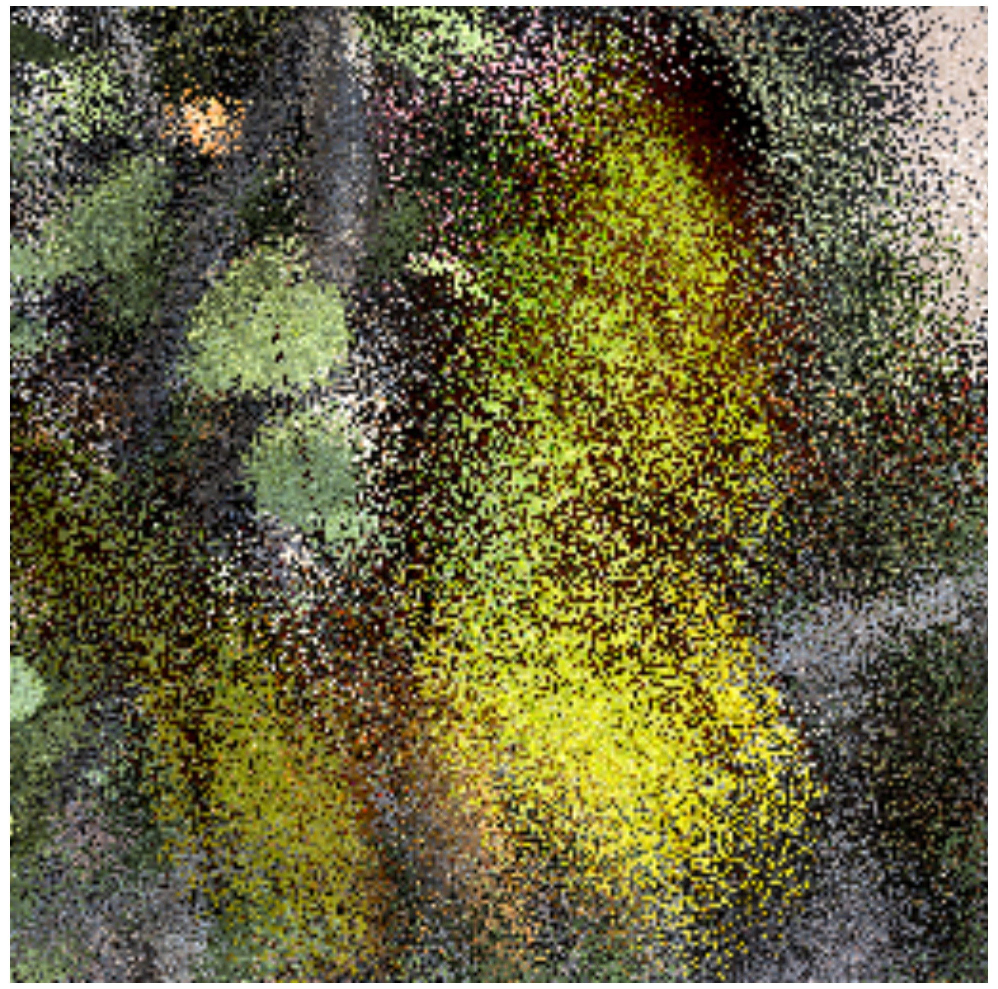
Slides courtesy: Stanford Online Course

Machine Learning for Filtering Monte Carlo Noise

Kalantari et al. [SIGGRAPH 2015]

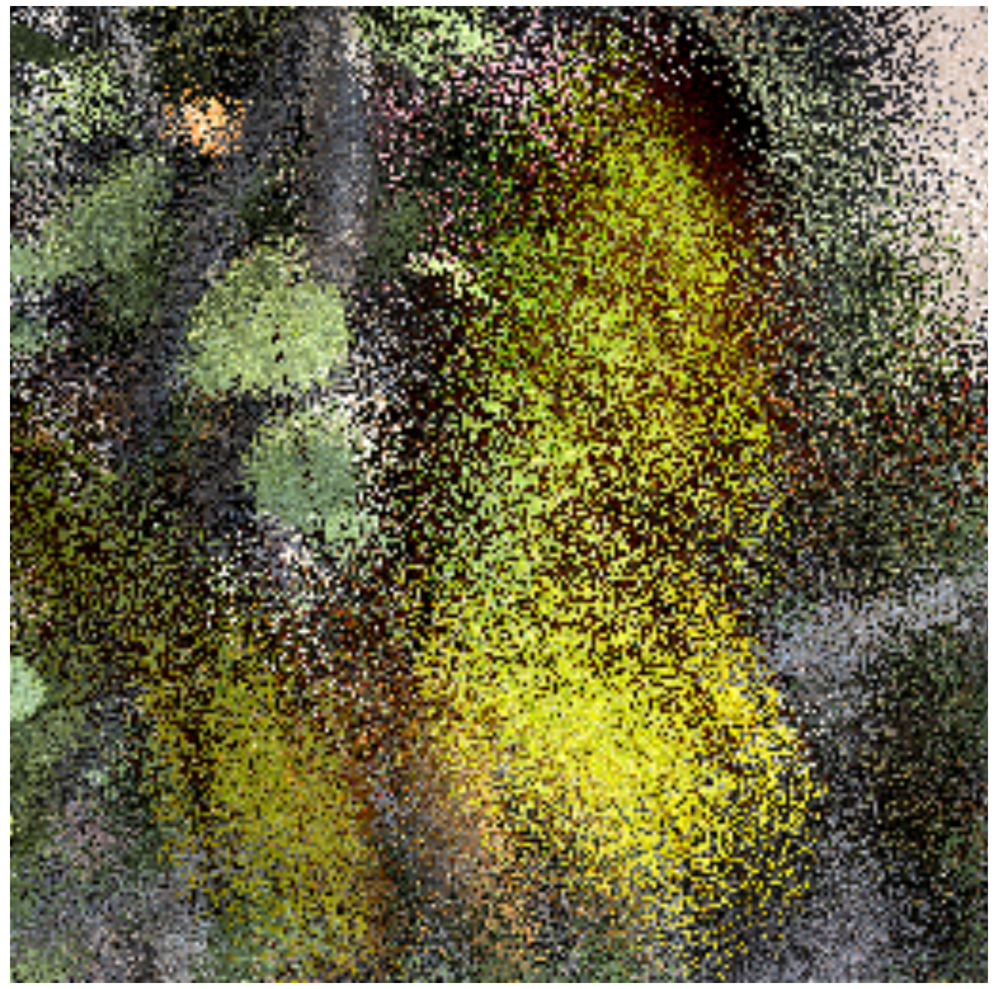
Reconstruction / Denoising

$$\hat{\mathbf{c}}_i = \frac{\sum_{j \in \mathcal{N}(i)} d_{i,j} \bar{\mathbf{c}}_j}{\sum_{j \in \mathcal{N}(i)} d_{i,j}} \quad , \quad \hat{\mathbf{c}} = \{\hat{c}_r, \hat{c}_g, \hat{c}_b\}$$



Reconstruction / Denoising

$$\hat{\mathbf{c}}_i = \frac{\sum_{j \in \mathcal{N}(i)} d_{i,j} \bar{\mathbf{c}}_j}{\sum_{j \in \mathcal{N}(i)} d_{i,j}} \quad , \quad \hat{\mathbf{c}} = \{\hat{c}_r, \hat{c}_g, \hat{c}_b\}$$



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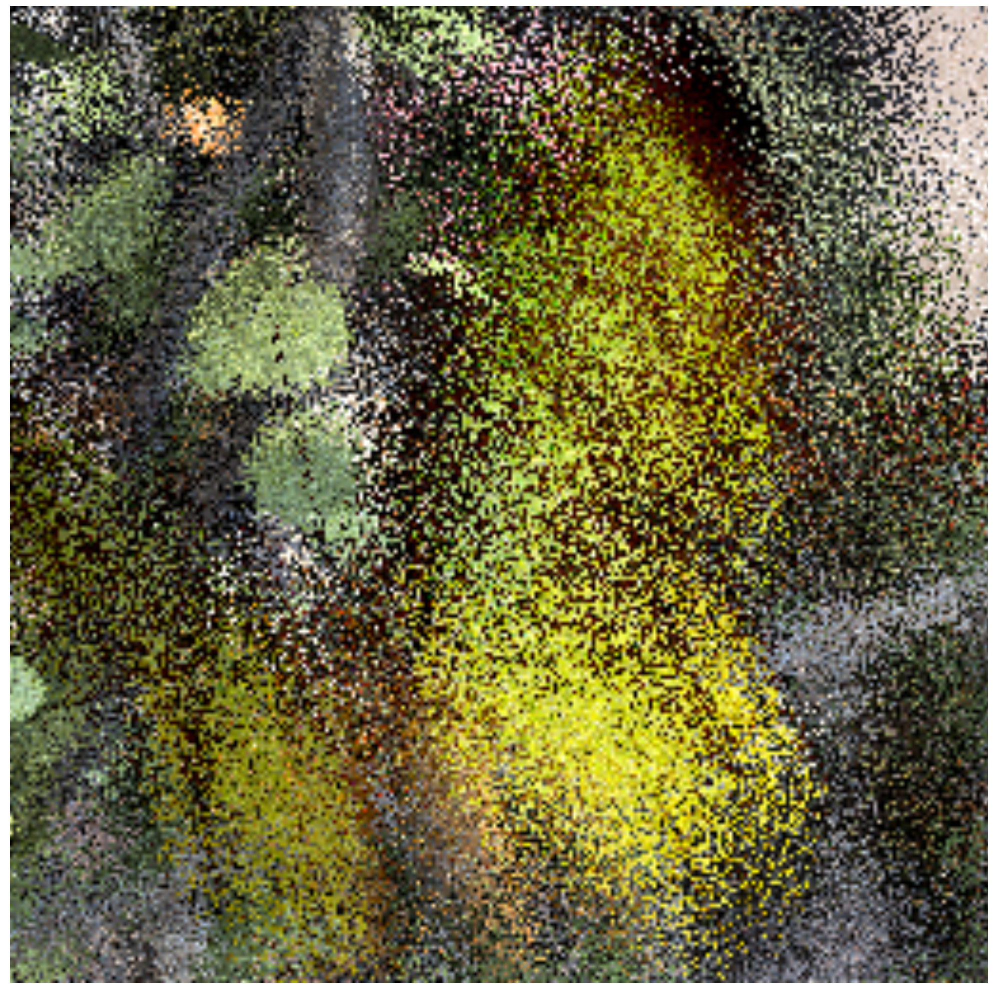
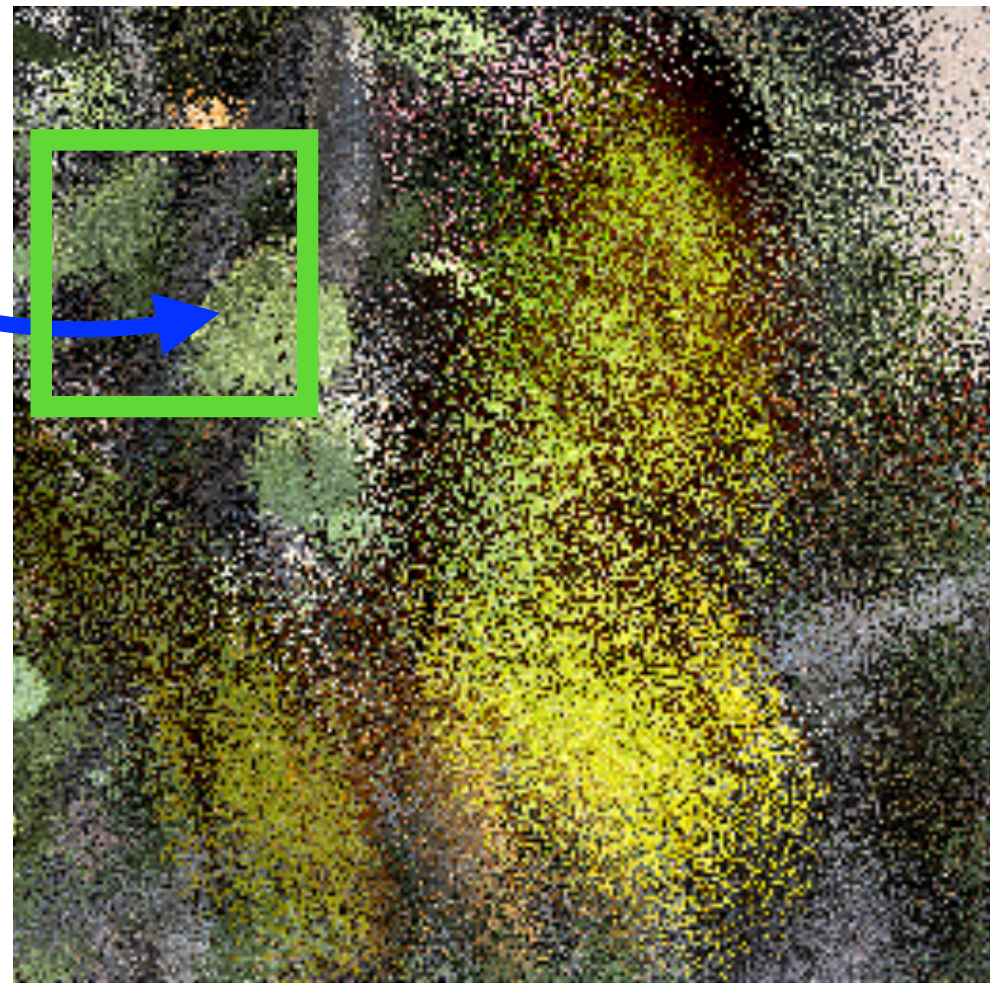
Pixel neighborhood



Reconstruction / Denoising

$$\hat{\mathbf{c}}_i = \frac{\sum_{j \in \mathcal{N}(i)} d_{i,j} \bar{\mathbf{c}}_j}{\sum_{j \in \mathcal{N}(i)} d_{i,j}}, \quad \hat{\mathbf{c}} = \{\hat{c}_r, \hat{c}_g, \hat{c}_b\}$$

Pixel neighborhood

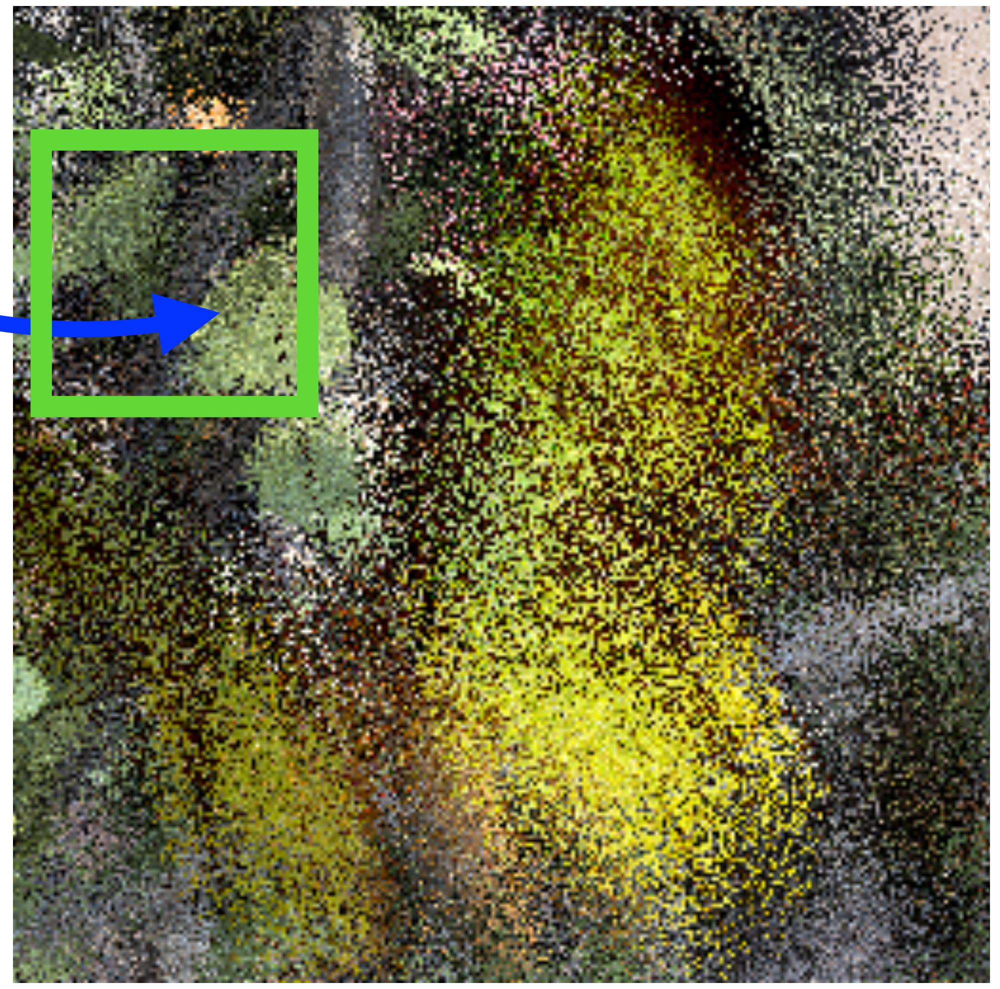


Reconstruction / Denoising

Filter weights

$$\hat{\mathbf{c}}_i = \frac{\sum_{j \in \mathcal{N}(i)} d_{i,j} \bar{\mathbf{c}}_j}{\sum_{j \in \mathcal{N}(i)} d_{i,j}}, \quad \hat{\mathbf{c}} = \{\hat{c}_r, \hat{c}_g, \hat{c}_b\}$$

Pixel neighborhood



Filter weights

Filter weights

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Pixel neighborhood

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Pixel neighborhood

For cross Bilateral filters:

Filter weights

Filter weights

$$\hat{\mathbf{c}}_i = \frac{\sum_{j \in \mathcal{N}(i)} d_{i,j} \bar{\mathbf{c}}_j}{\sum_{j \in \mathcal{N}(i)} d_{i,j}}$$

Pixel neighborhood

For cross Bilateral filters:

$$d_{i,j} = \exp\left[-\frac{\|\bar{\mathbf{p}}_i - \bar{\mathbf{p}}_j\|^2}{2\alpha_i^2}\right] \times \exp\left[-\frac{D(\bar{\mathbf{c}}_i, \bar{\mathbf{c}}_j)}{2\beta_i^2}\right] \times \prod_{k=1}^{K} \exp\left[-\frac{D_k(\bar{\mathbf{f}}_{i,k}, \bar{\mathbf{f}}_{j,k})}{2\gamma_{k,i}^2}\right],$$

Filter weights

Filter weights

$$\hat{\mathbf{c}}_i = \frac{\sum_{j \in \mathcal{N}(i)} d_{i,j} \bar{\mathbf{c}}_j}{\sum_{j \in \mathcal{N}(i)} d_{i,j}}$$

Pixel neighborhood

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Sen and Darabi [2012]

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Sen and Darabi [2012]

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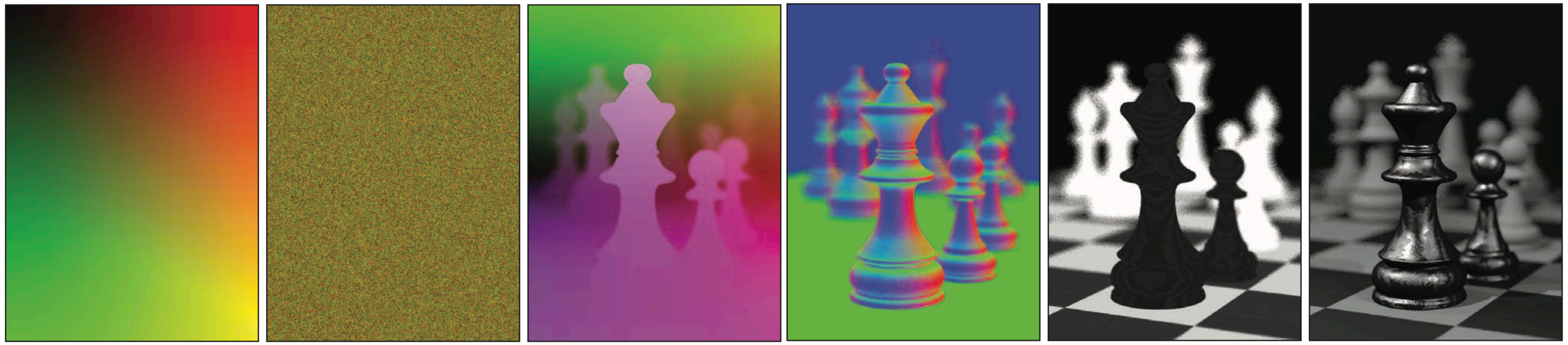


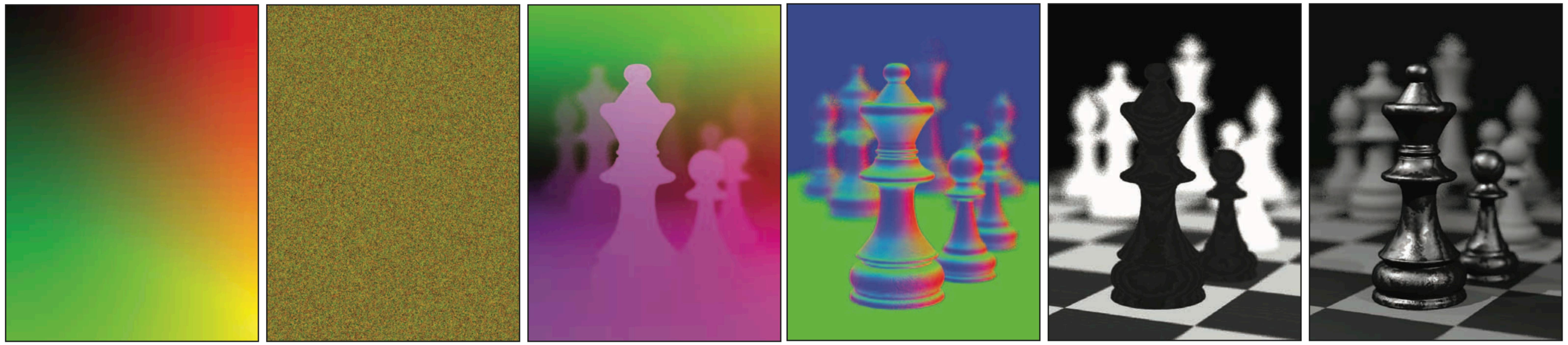
(a) Screen position **(b)** Random parameters **(c)** World space coords. **(d)** Surface normals **(e)** Texture value **(f)** Sample color

Filter weights

For cross Bilateral filters:

Pixel screen coordinates

$$d_{i,j} = \exp\left[-\frac{\|\bar{\mathbf{p}}_i - \bar{\mathbf{p}}_j\|^2}{2\alpha_i^2}\right] \times \exp\left[-\frac{D(\bar{\mathbf{c}}_i, \bar{\mathbf{c}}_j)}{2\beta_i^2}\right] \times \prod_{k=1}^{K} \exp\left[-\frac{D_k(\bar{\mathbf{f}}_{i,k}, \bar{\mathbf{f}}_{j,k})}{2\gamma_{k,i}^2}\right],$$



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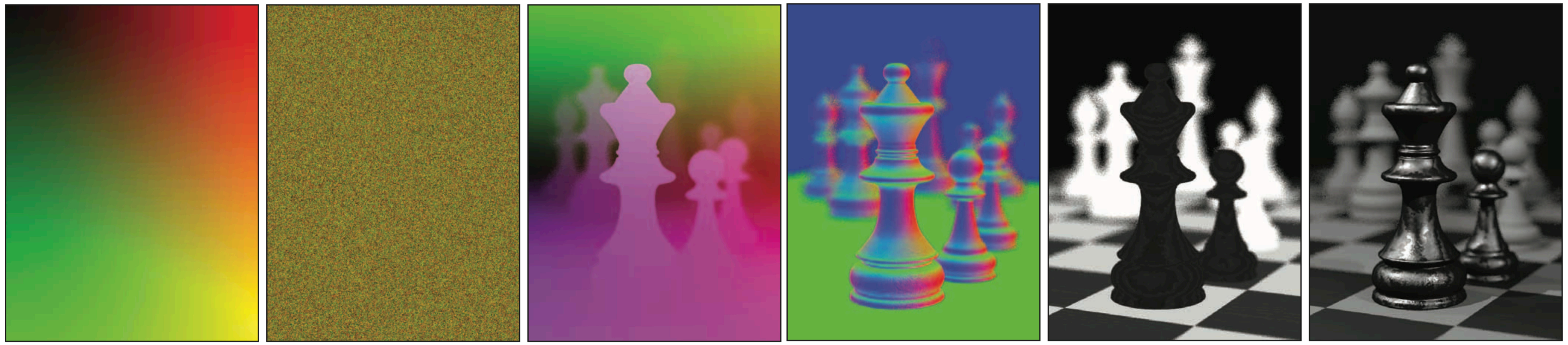
$$\times \prod_{k=1}^{K} \exp\left[-\frac{D_k(\bar{\mathbf{f}}_{i,k}, \bar{\mathbf{f}}_{j,k})}{2\gamma_{k,i}^2}\right],$$

Pixel screen coordinates

Mean sample color value



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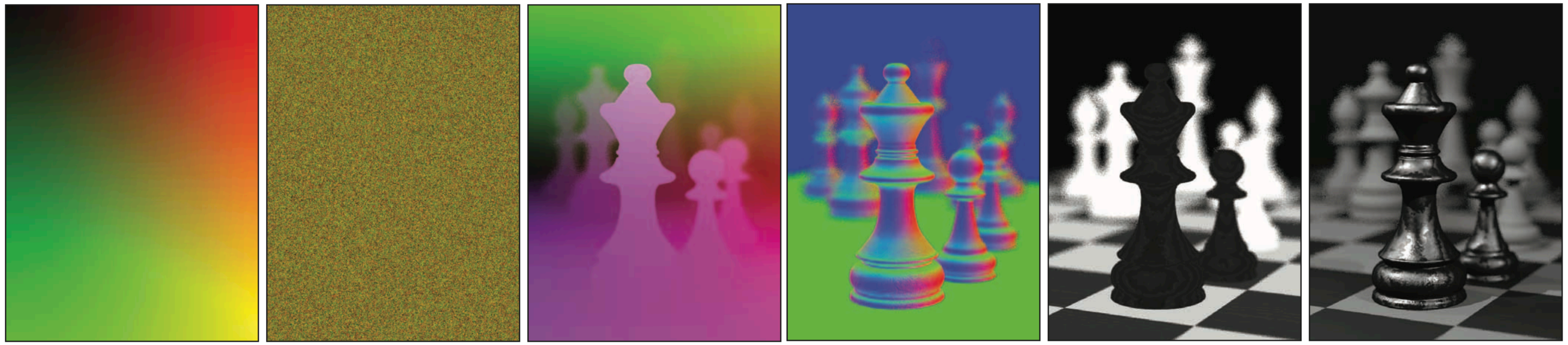
Pixel screen coordinates

Mean sample color value

Scene features



(a) Screen position **(b)** Random parameters **(c)** World space coords. **(d)** Surface normals **(e)** Texture value **(f)** Sample color

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Pixel screen coordinates

Mean sample color value

Scene features

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Pixel screen coordinates

Mean sample color value

Scene features

What are the **optimal** parameters ?

Neural Network Approach

- Feed-forward Neural network
- Best part: We can learn weights in a training phase
- Back propagation: Important for training weights
- For Back propagation, the Loss function should be differentiable and
- all the intermediate functionals should be differentiable.

One Hidden-layer model

Relative Mean Square Error:

$$E_i = \frac{n}{2} \sum_{q \in \{r,g,b\}} \frac{\left(\hat{c}_{i,q} - c_{i,q}\right)^2}{c_{i,q}^2 + \varepsilon}$$

One Hidden-layer model

Relative Mean Square Error:

$$\frac{\partial E_i}{\partial w_{t,s}^l} = \sum_{m=1}^{M} \left[\sum_{q \in \{r,g,b\}} \left[\frac{\partial E_{i,q}}{\partial \hat{c}_{i,q}} \frac{\partial \hat{c}_{i,q}}{\partial \theta_{m,i}} \right] \frac{\partial \theta_{m,i}}{\partial w_{t,s}^l} \right]$$

$$E_i = \frac{n}{2} \sum_{q \in \{r,g,b\}} \frac{\left(\hat{c}_{i,q} - c_{i,q}\right)^2}{c_{i,q}^2 + \varepsilon}$$

$$\frac{\partial E_i}{\partial \hat{c}_{i,q}} = ???$$

One Hidden-layer model

Relative Mean Square Error:

$$\frac{\partial E_i}{\partial w_{t,s}^l} = \sum_{m=1}^{M} \left[\sum_{q \in \{r,g,b\}} \left[\frac{\partial E_{i,q}}{\partial \hat{c}_{i,q}} \frac{\partial \hat{c}_{i,q}}{\partial \theta_{m,i}} \right] \frac{\partial \theta_{m,i}}{\partial w_{t,s}^l} \right]$$

$$E_i = \frac{n}{2} \sum_{q \in \{r,g,b\}} \frac{\left(\hat{c}_{i,q} - c_{i,q}\right)^2}{c_{i,q}^2 + \varepsilon}$$

$$\frac{\partial E_i}{\partial \hat{c}_{i,q}} = n \frac{\hat{c}_{i,q} - c_{i,q}}{c_{i,q}^2 + \epsilon}$$

Results


4spp
Input
MLP
GT


4spp
Input
MLP
GT

Introduction to CNNs

Introduction to CNNs

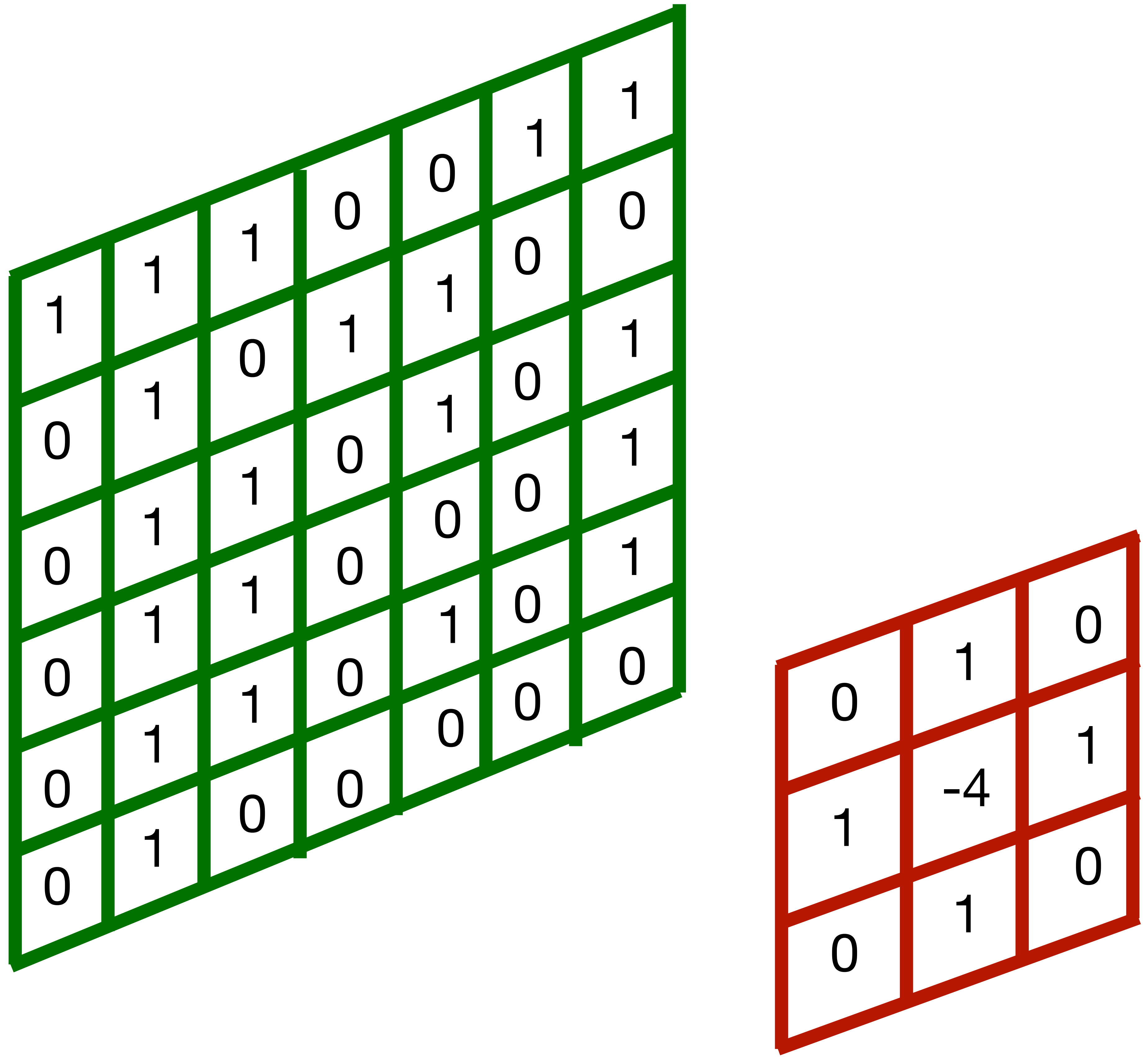
Kernel Predicting Denoising

Introduction to CNNs

Kernel Predicting Denoising

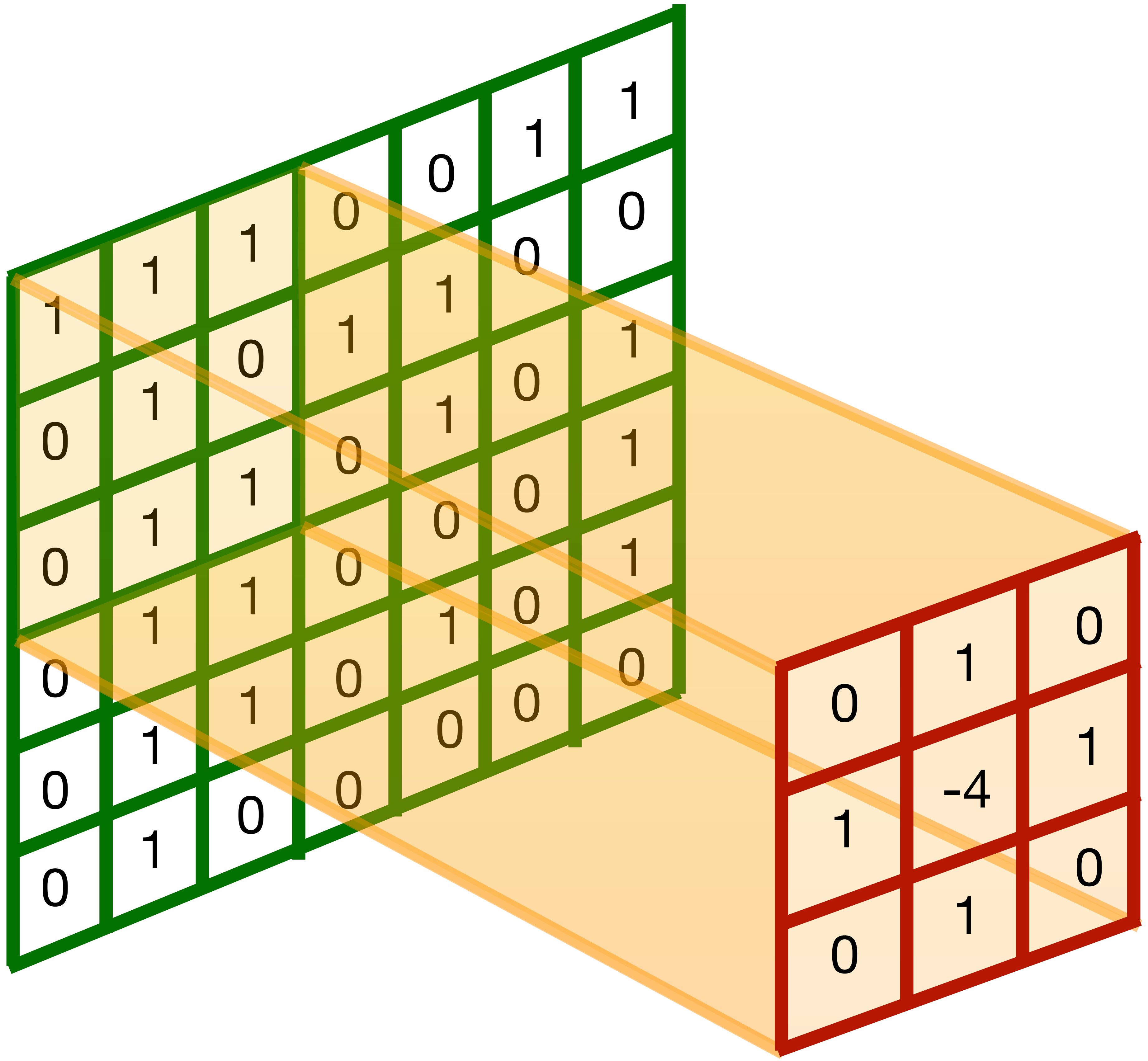
Sample-based MC Denoising

Convolution



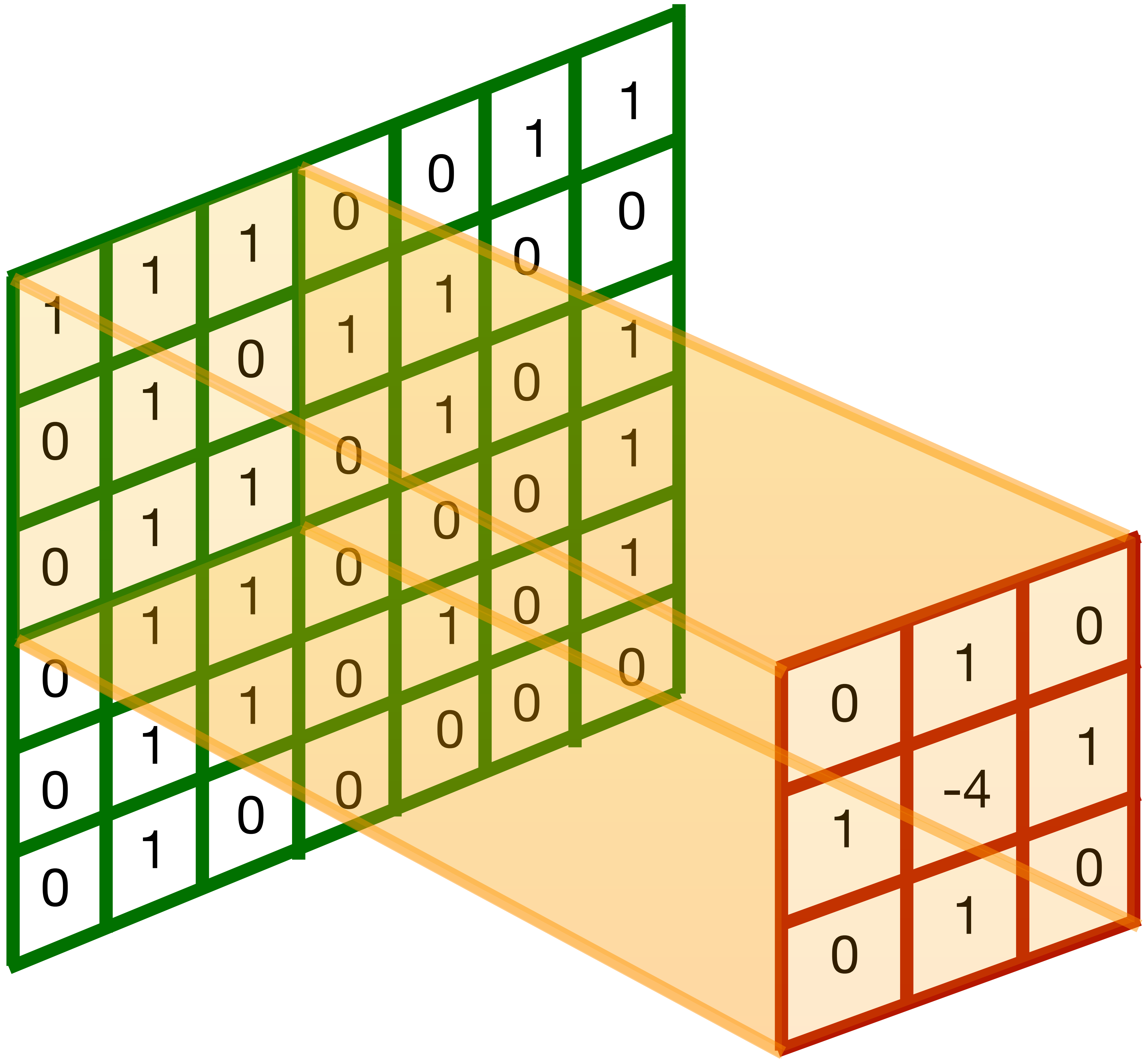
No zero padding

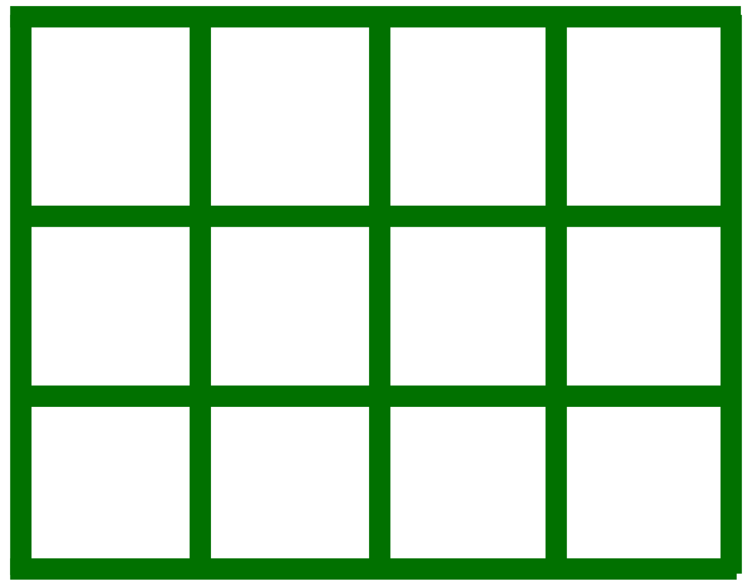
Convolution



No zero padding

Stride-1 Convolution





No zero padding

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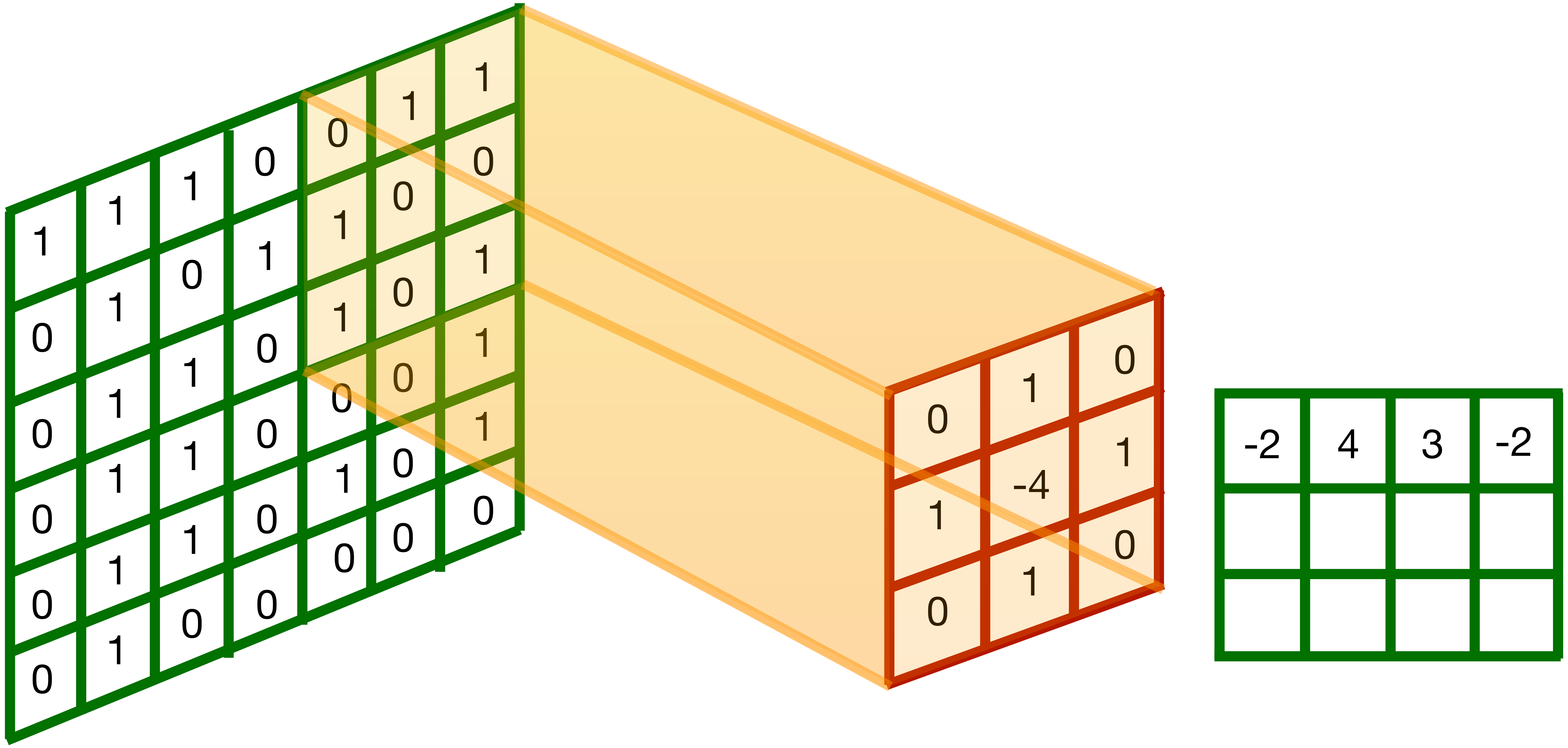

No zero padding

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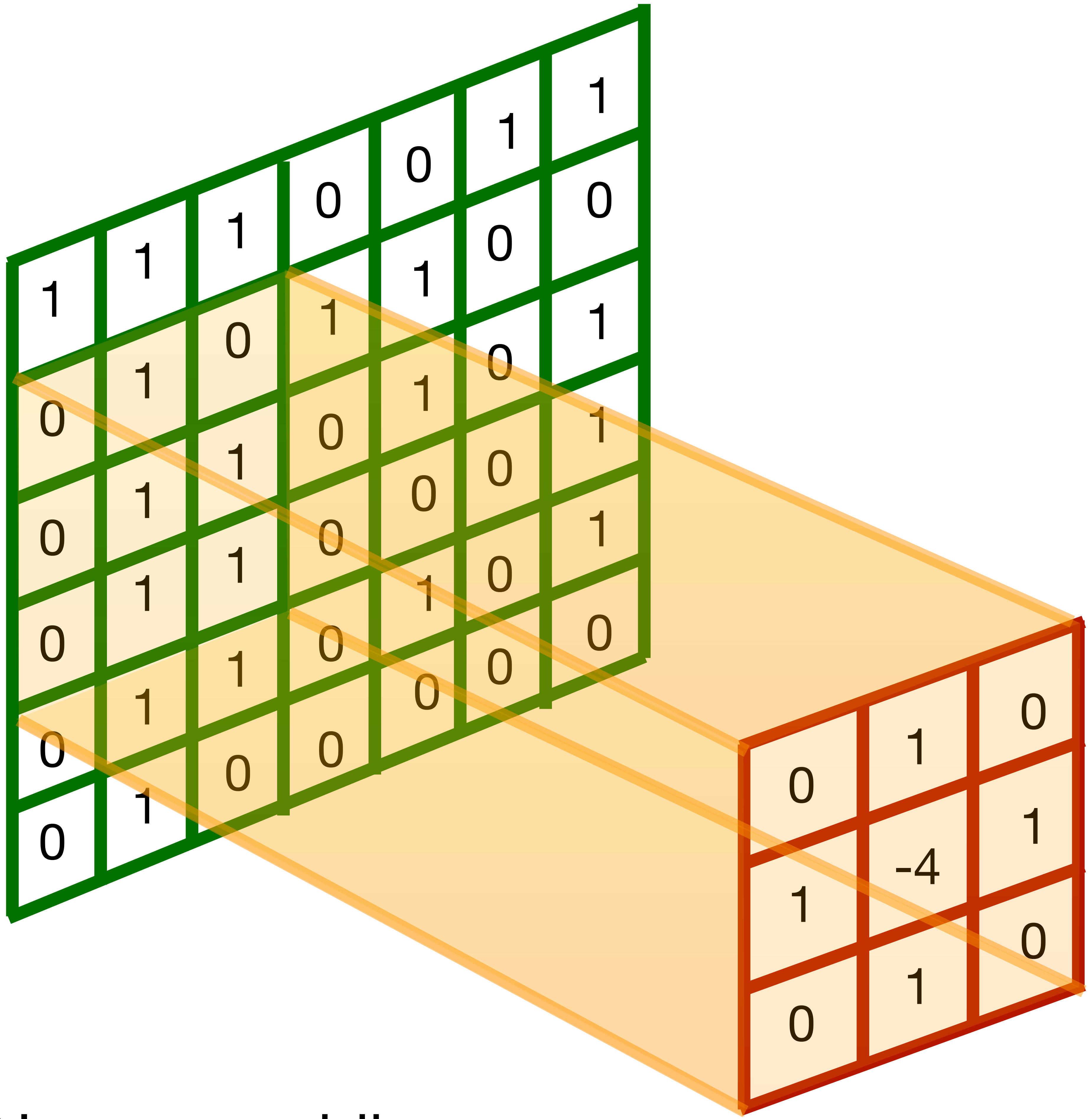
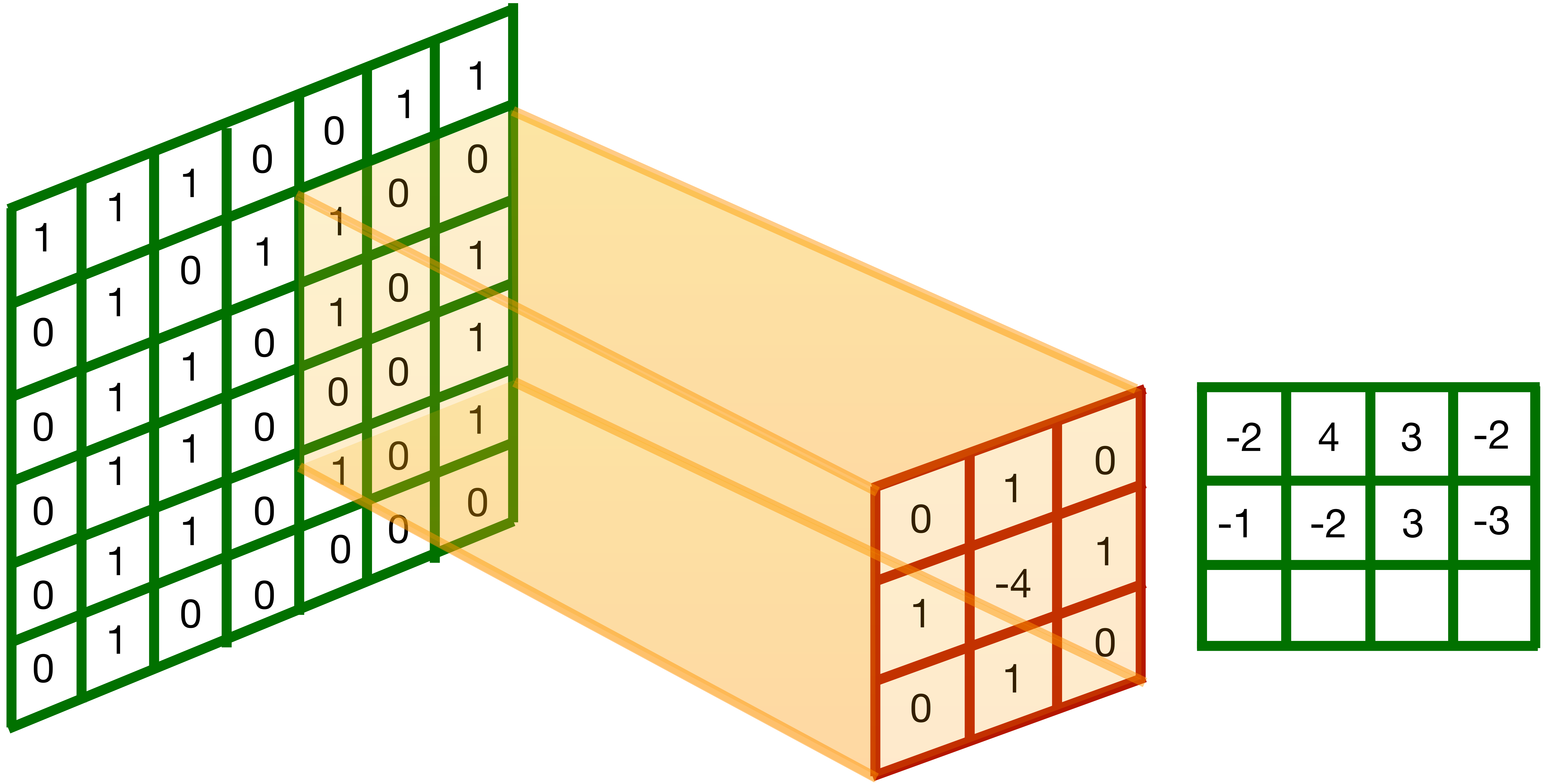


-2	4	3	-2

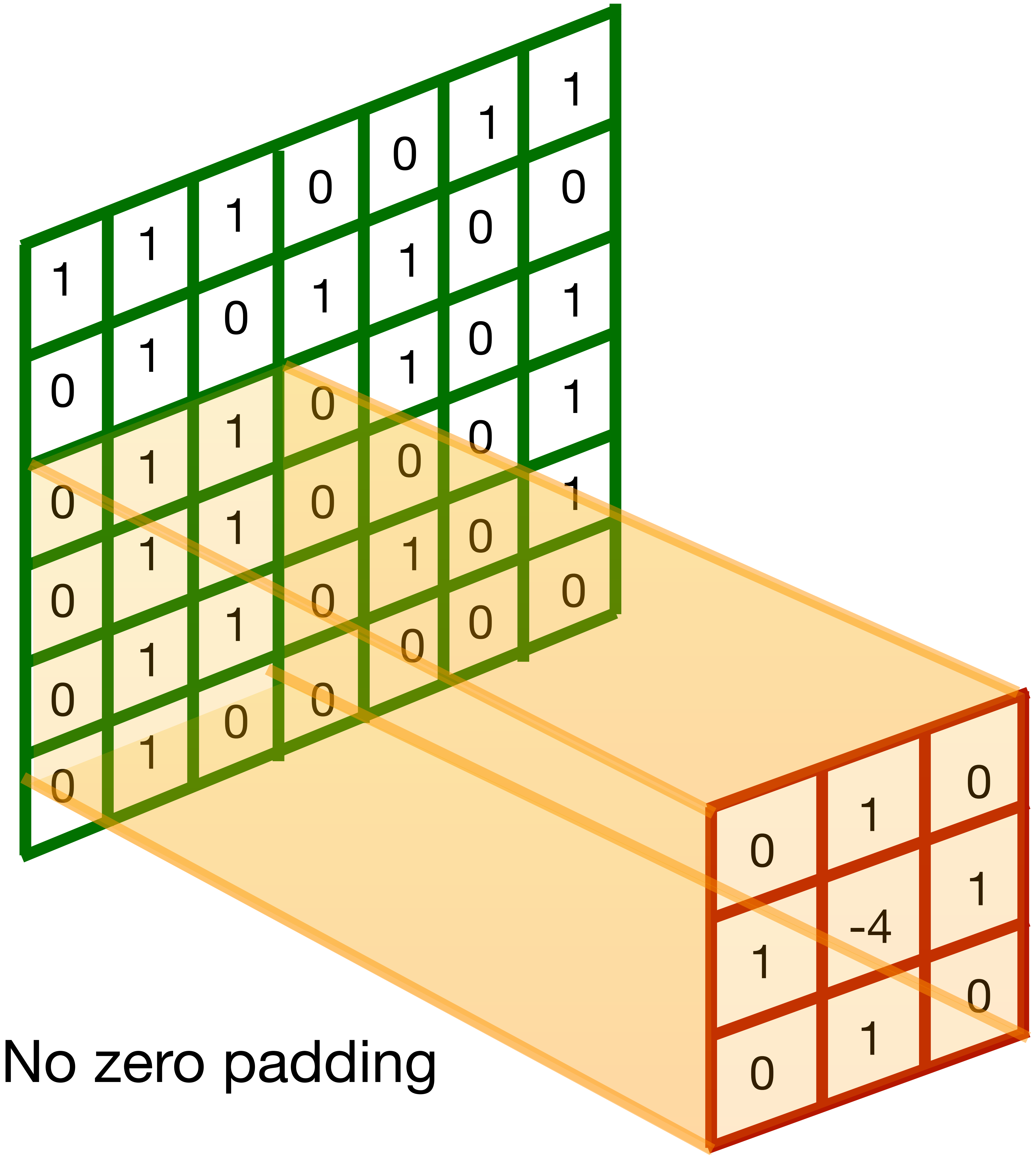
No zero padding

Stride-1 Convolution



No zero padding

Stride-1 Convolution

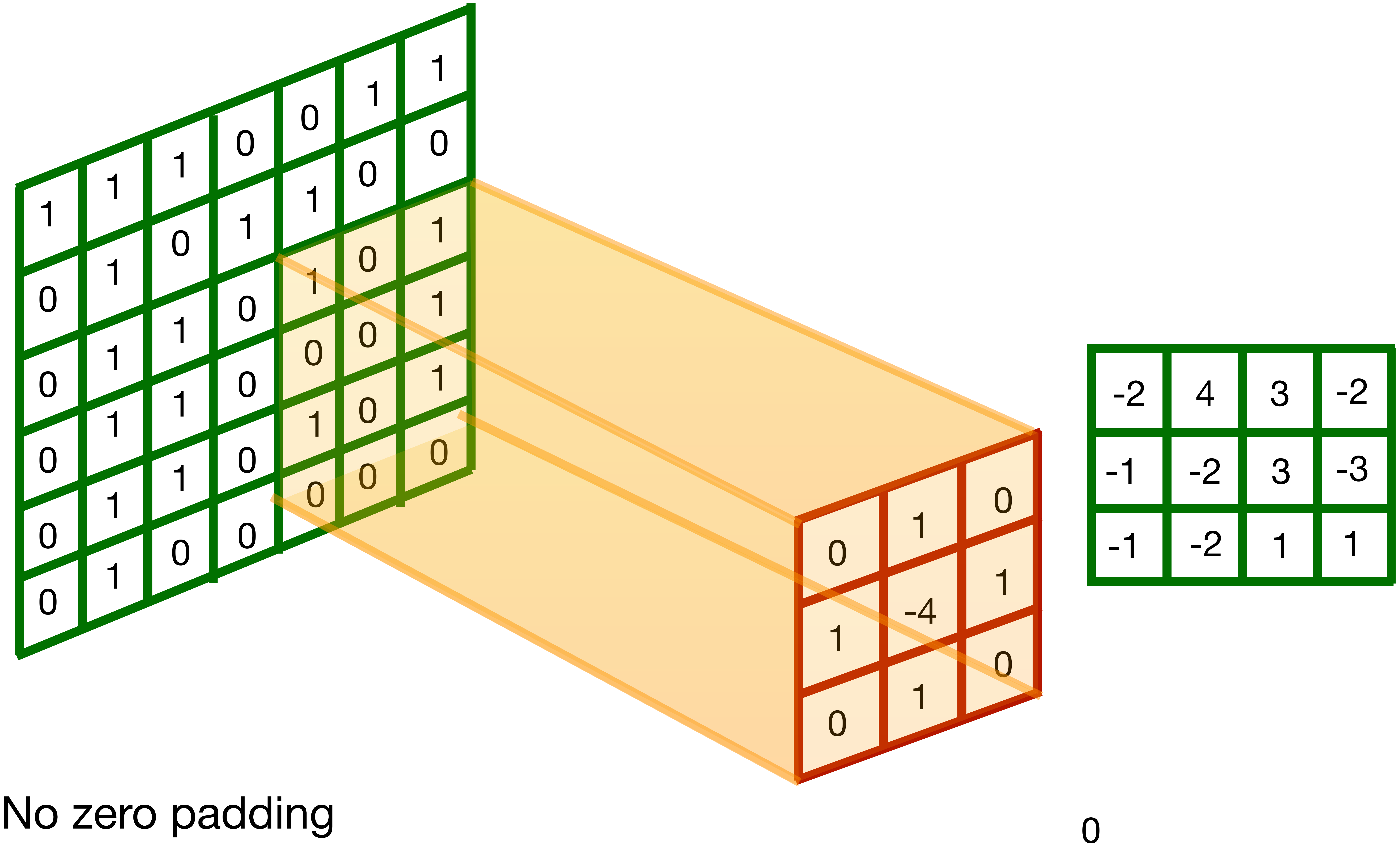


No zero padding

-2	4	3	-2
-1	-2	3	-3

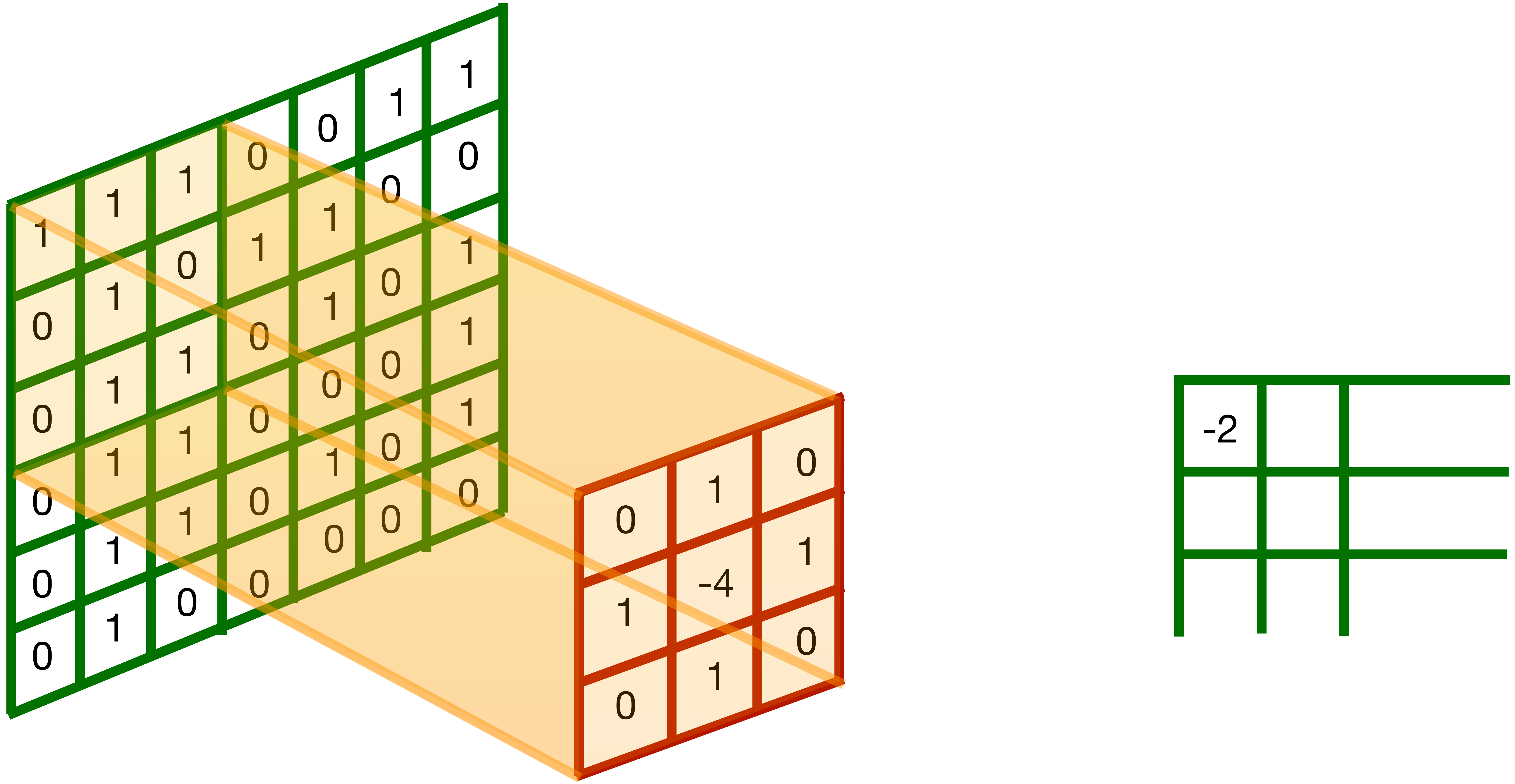
0

Stride-1 Convolution

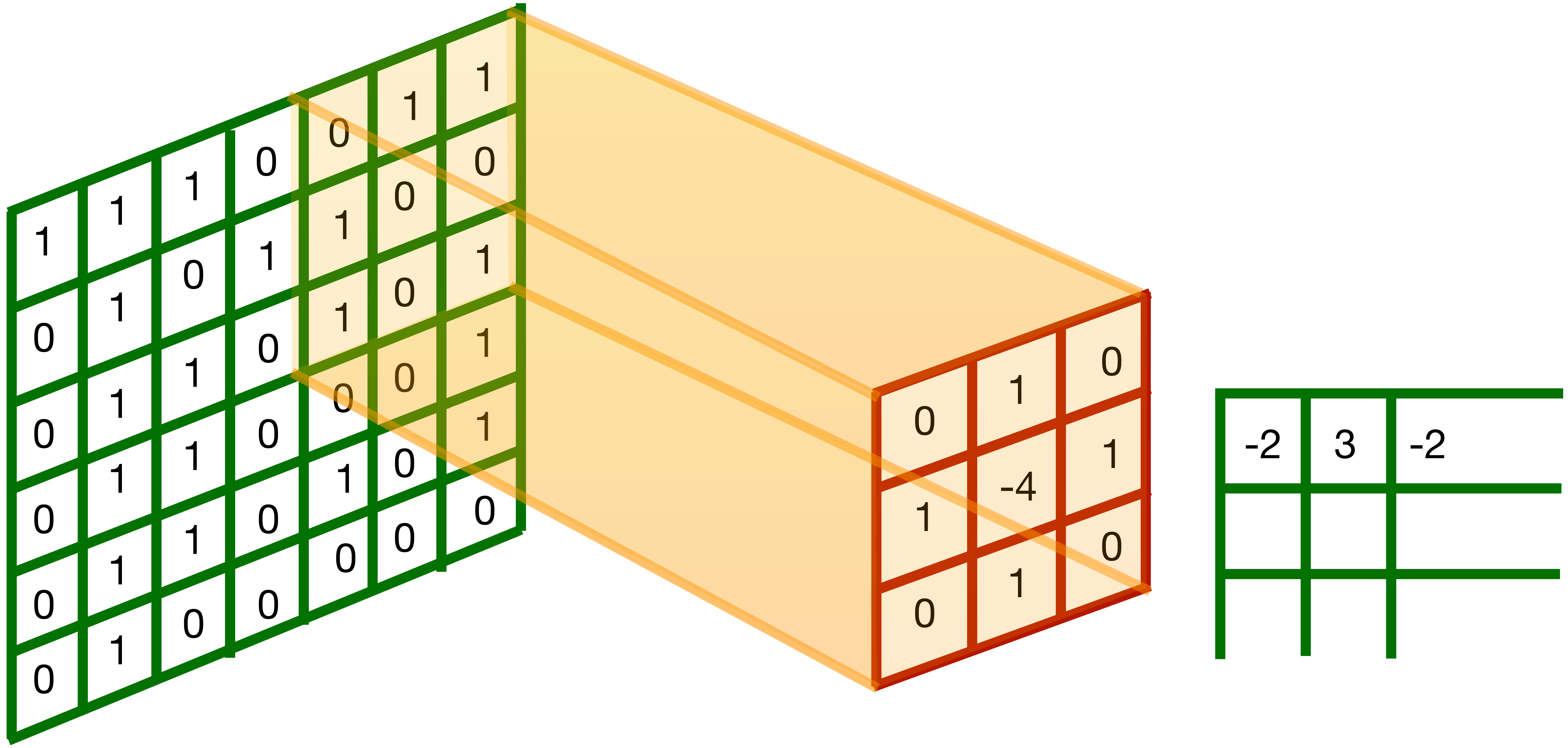


No zero padding

Stride-2 Convolution

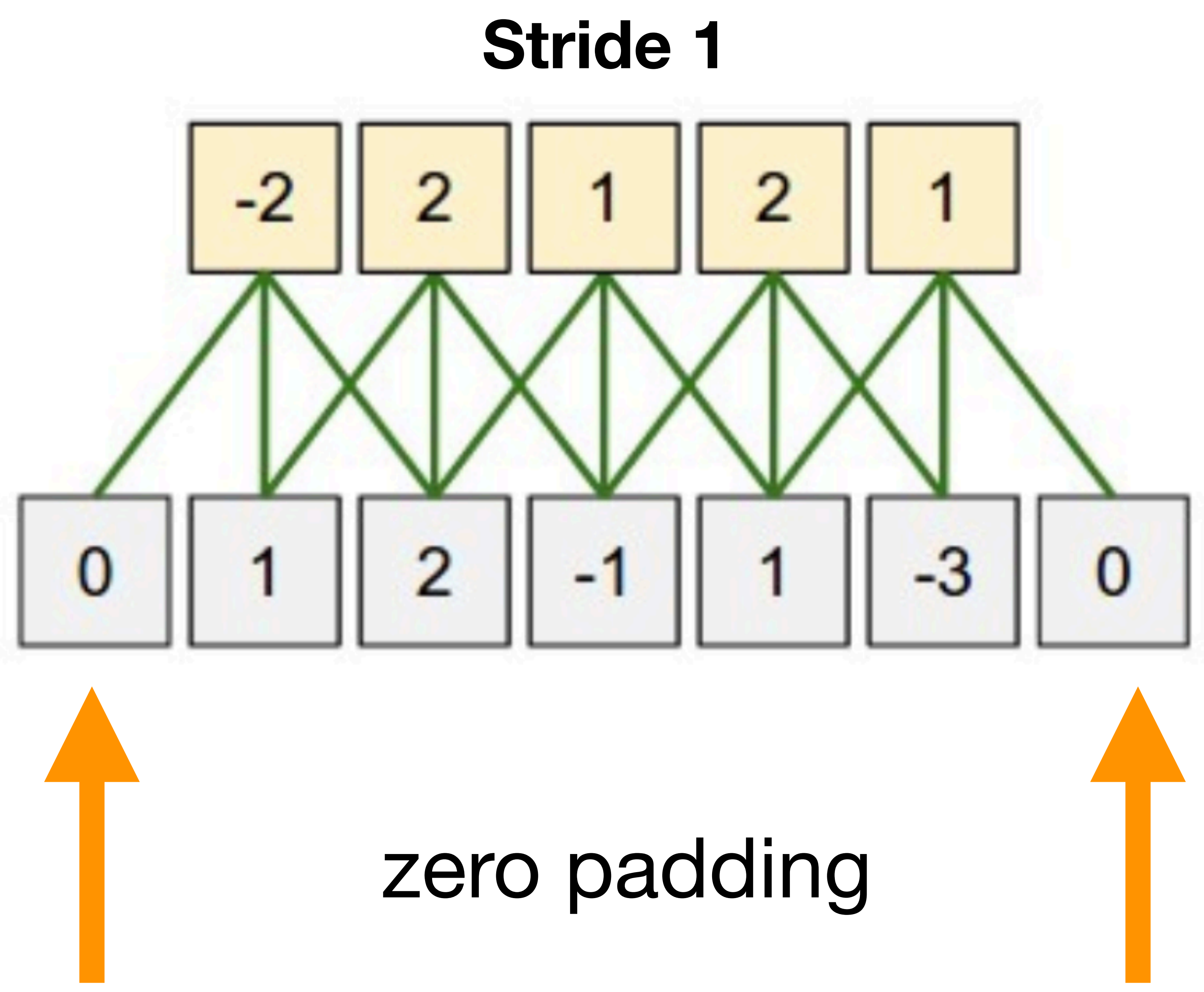


Stride-2 Convolution



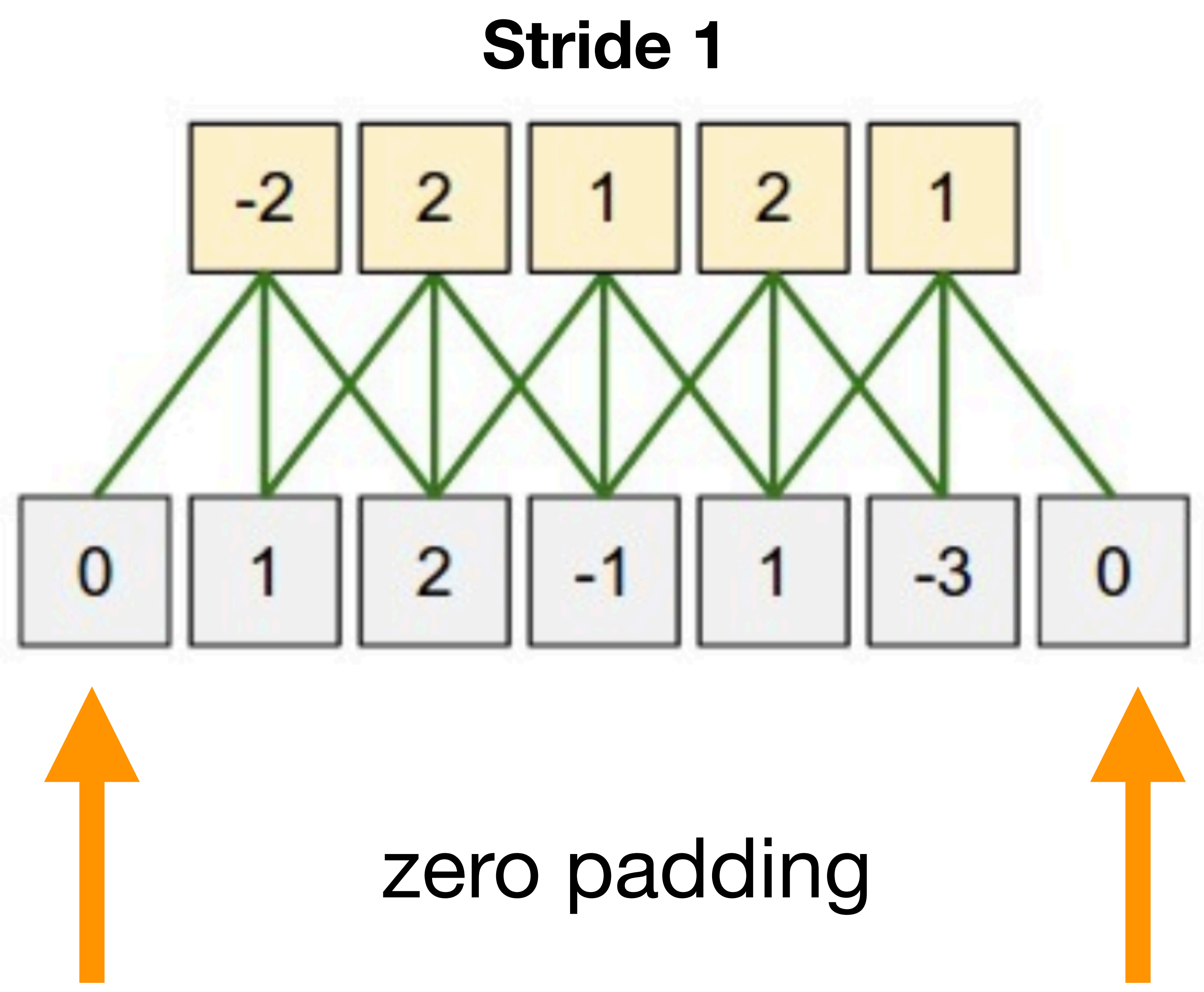
Zero Padding and Strides

1D image to illustrate the strides and zero padding



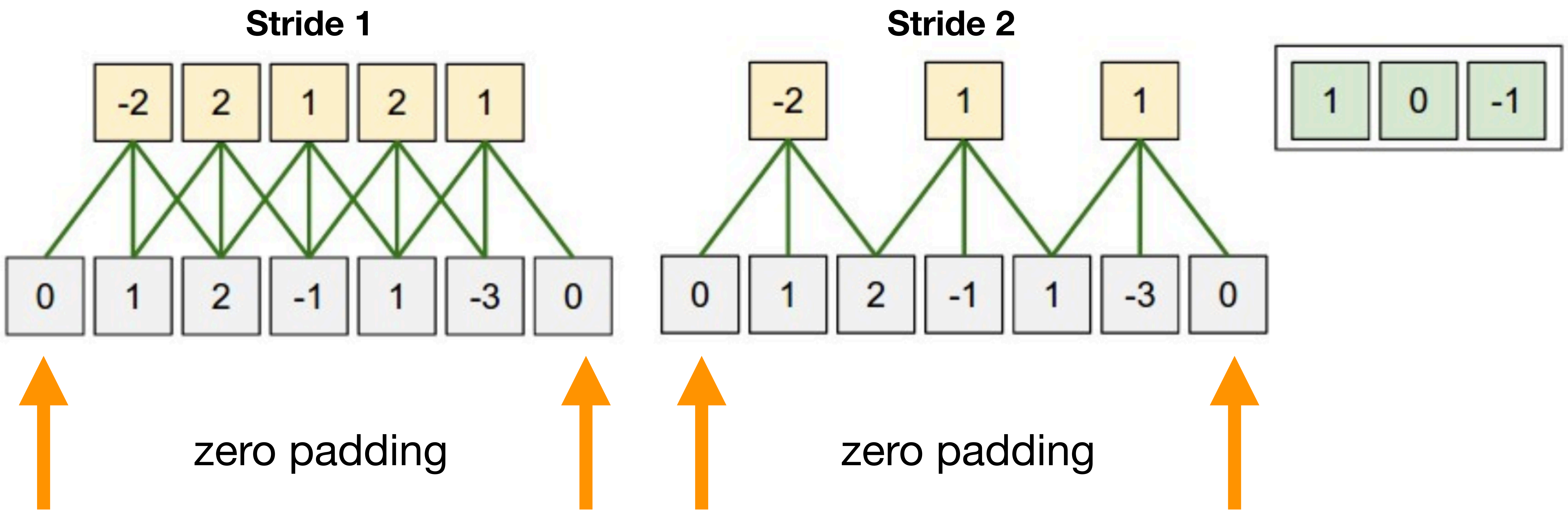
Zero Padding and Strides

1D image to illustrate the strides and zero padding

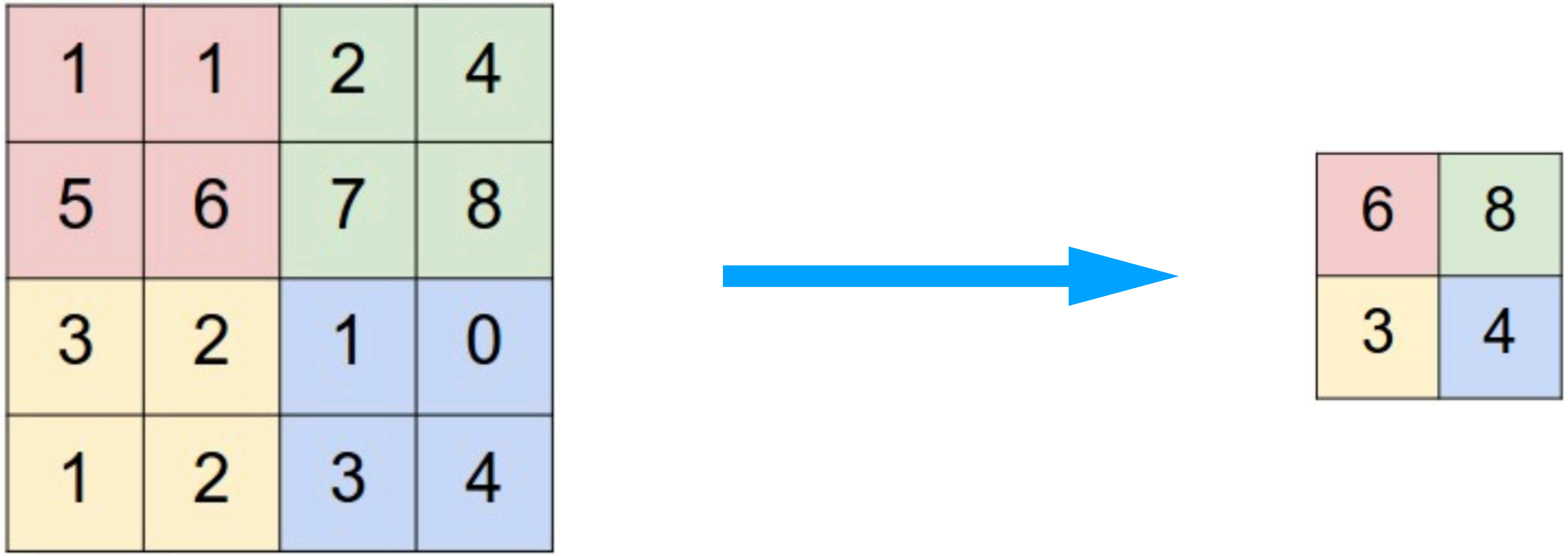


Strides

1D image to illustrate the strides and zero padding



Max Pooling / Down Sampling



Overview on Convolutional Neural Networks

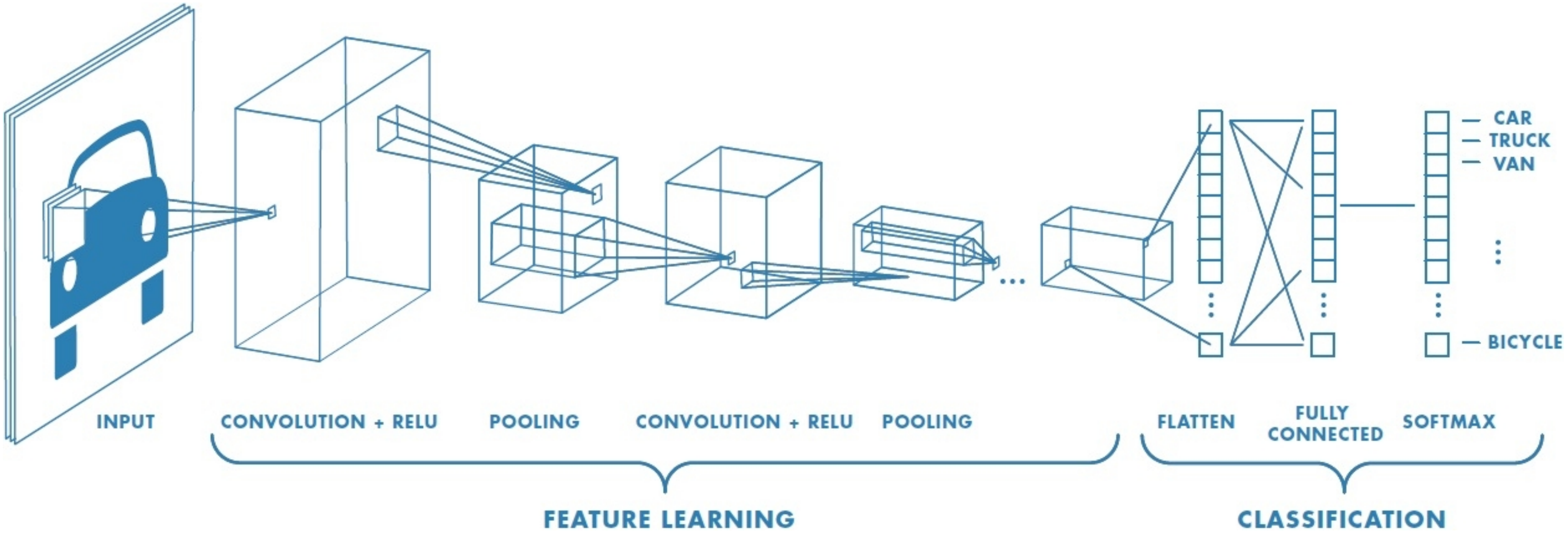
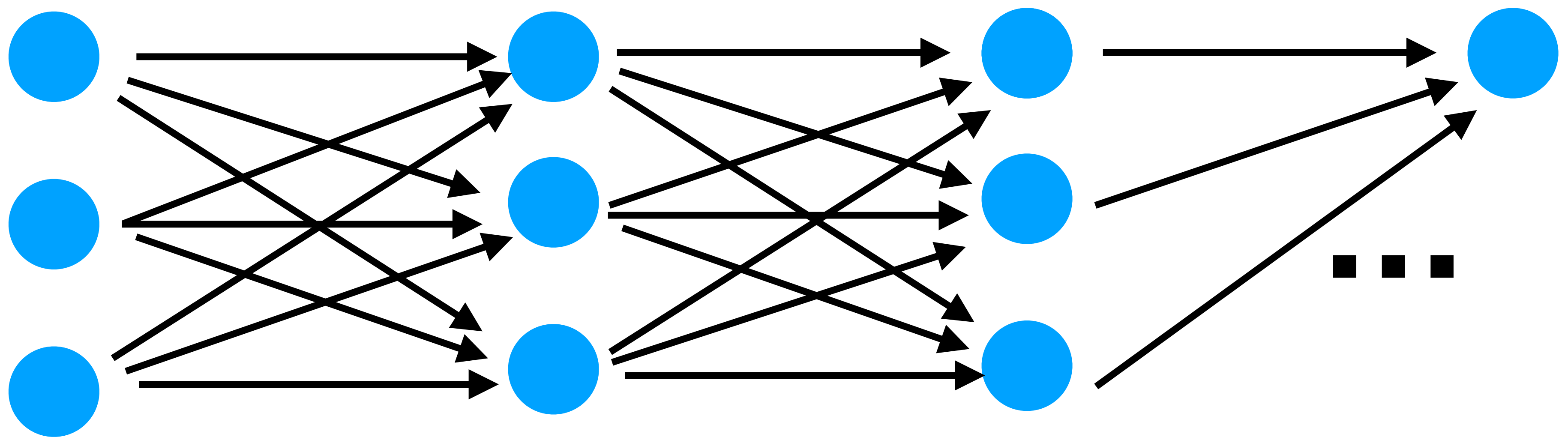


Image Courtesy: Mathworks (online tutorial)

Multi-layer Perceptron vs. CNNs

Multi-layer Perceptron vs. CNNs

Multi-layer perceptron

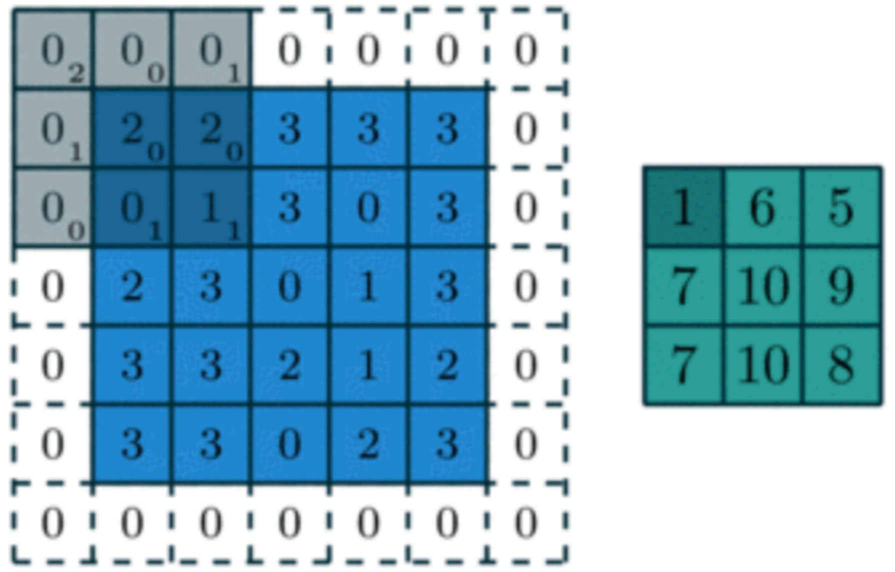


All nodes are fully connected in all layers

In theory, should be able to achieve good quality results in small number of layers.

Number of weights to be learnt are very high

CNNs



Weights are shared across layers

Requires significant number of layers to capture all the features (e.g. Deep CNNs)

Relatively small number of weights required

Introduction to CNNs

Kernel-Predicting Denoising

Kernel-Predicting Networks for Denoising Monte-Carlo Renderings

Bako et al. [2017]

Limitations of MLP based Denoiser

Kernel was pre-selected to be joint bilateral filter

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Fixed

- can cause unstable weights causing bright ringing and color artifacts

Too many parameters to optimize

Requirements

The function must be flexible to capture complex relationship between input data and reference colors over wide range of scenarios.

Choice of loss function is crucial. Should capture perceptual aspects of the scene.

To avoid overfitting, large dataset required

Using a Vanilla CNN

Denoising a raw, noisy color buffer causes overblurring

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- difficulty in distinguishing scene details and MC noise

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High dynamic range

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High dynamic range

- can cause unstable weights causing bright ringing and color artifacts

Vanilla CNN

Ours | Input (32 spp) | Vanilla CNN | Ours | Ref. (1K spp)

Denoising Model

$$\widehat{\boldsymbol{\theta}}_p = \underset{\boldsymbol{\theta}}{\operatorname{argmin}}\, \ell(\overline{\mathbf{c}}_p, g(\mathbf{X}_p; \boldsymbol{\theta}))$$

Denoised function with parameters

Reference image

$$\widehat{\mathbf{c}}_p = g(\mathbf{X}_p; \widehat{\boldsymbol{\theta}}_p)$$

Denoised value

$$\ell(\overline{\mathbf{c}}, \widehat{\mathbf{c}})$$

Loss function

Computational Model

$$\widehat{\boldsymbol{\theta}}_p = \underset{\boldsymbol{\theta}}{\operatorname{argmin}} \sum_{q \in \mathcal{N}(p)} \left(\mathbf{c}_q - \boldsymbol{\theta}^\top \phi(\mathbf{x}_q)\right)^2 \omega(\mathbf{x}_p, \mathbf{x}_q)$$

Neighborhood

$$\widehat{\mathbf{c}}_p = g(\mathbf{X}_p; \widehat{\boldsymbol{\theta}}_p)$$

Denoised value

$$\phi : \mathbb{R}^{3+D} \to \mathbb{R}^M$$

$\omega(\mathbf{x}_p, \mathbf{x}_q)$ Kernel weights

$$\widehat{\mathbf{c}}_p = \widehat{\boldsymbol{\theta}}_p^\top \phi(\mathbf{x}_p)$$

Final denoised value

Direct Prediction Network

Direct prediction convolution network: outputs denoised image

$$\widehat{\mathbf{c}}_p = g_{\text{direct}}(\mathbf{X}_p; \boldsymbol{\theta}) = \mathbf{z}_p^L$$

Direct Prediction Network

Direct prediction convolution network: outputs denoised image

$$\widehat{\mathbf{c}}_p = g_{\text{direct}}(\mathbf{X}_p; \boldsymbol{\theta}) = \mathbf{z}_p^L$$

Issues:

The constrained nature and complexity of the problem makes optimization difficult.

The magnitude and variance of stochastic gradients computed during training can be large, which slows convergence of training loss.

Kernel Prediction Network

Kernel prediction convolution network: outputs learned kernel weights

$$w_{pq} = \frac{\exp([\mathbf{z}_p^L]_q)}{\sum_{q' \in \mathcal{N}(p)} \exp([\mathbf{z}_p^L]_{q'})}$$

$$0 \leq w_{pq} \leq 1$$

Softmax activation to enforce weights within range

Denoised color values:

$$\widehat{\mathbf{c}}_p = g_{\text{weighted}}(\mathbf{X}_p; \theta) = \sum_{q \in \mathcal{N}(p)} \mathbf{c}_q w_{pq}$$

Kernel Prediction Network

$$w_{pq} = \frac{\exp([\mathbf{z}_p^L]_q)}{\sum_{q' \in \mathcal{N}(p)} \exp([\mathbf{z}_p^L]_{q'})}$$

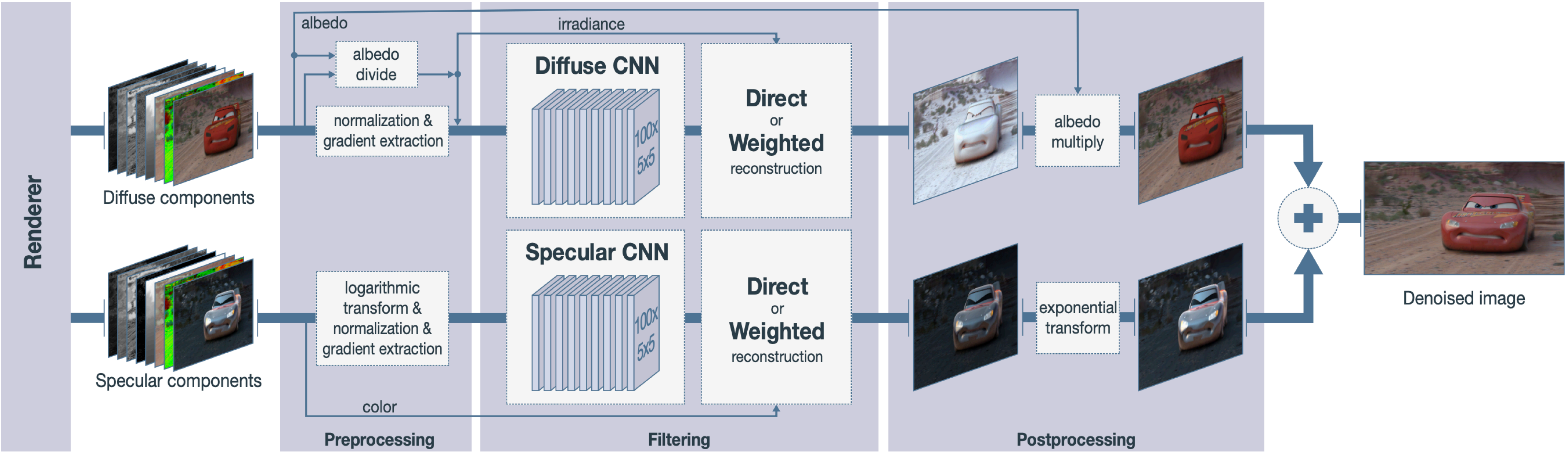
$$0 \leq w_{pq} \leq 1$$

$$\widehat{\mathbf{c}}_p = g_{\text{weighted}}(\mathbf{X}_p; \boldsymbol{\theta}) = \sum_{q \in \mathcal{N}(p)} \mathbf{c}_q w_{pq}$$

Final color estimate always lies within the convex hull of the respective neighborhood (avoid color shifts).

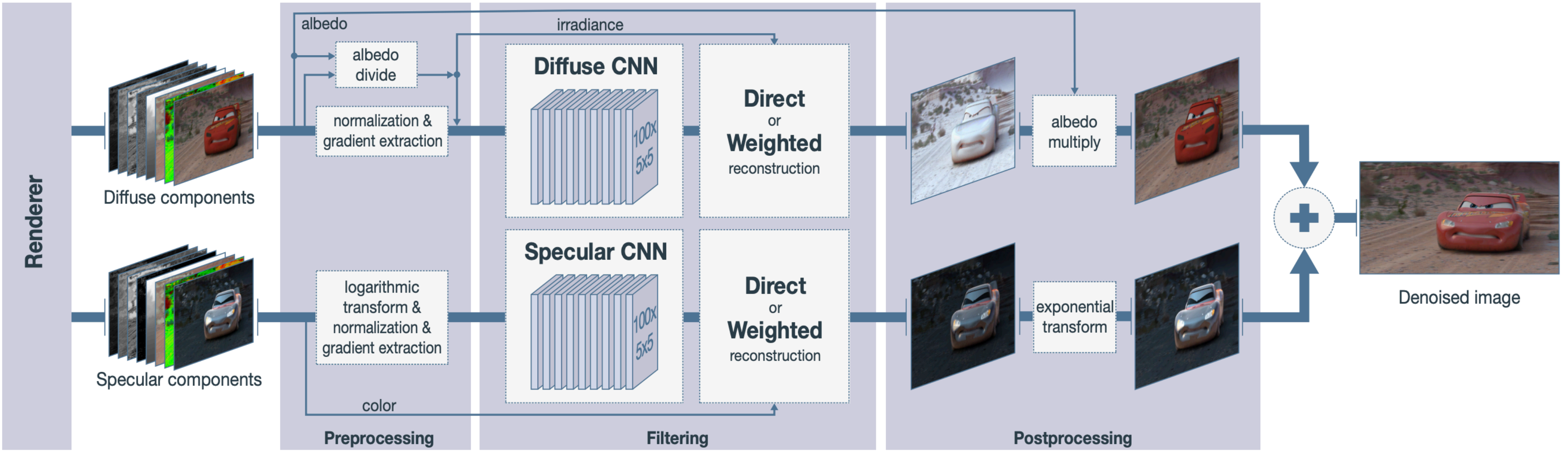
Ensures well-behaved gradients of the error w.r.t the kernel weights

Proposed Architecture



Diffuse/Specular components

Each component is denoised separately



Diffuse components are well-behaved and typically has small ranges

- albedo is factored out to allow large range kernels $\widetilde{\mathbf{c}}_{\text{diffuse}} = \mathbf{c}_{\text{diffuse}} \oslash (\mathbf{f}_{\text{albedo}} + \epsilon)$

Specular components are challenging due to high dynamic ranges: uses logarithmic transform

$$\widetilde{\mathbf{c}}_{\text{specular}} = \log(1 + \mathbf{c}_{\text{specular}})$$


Training Dataset: 600 frames

Training

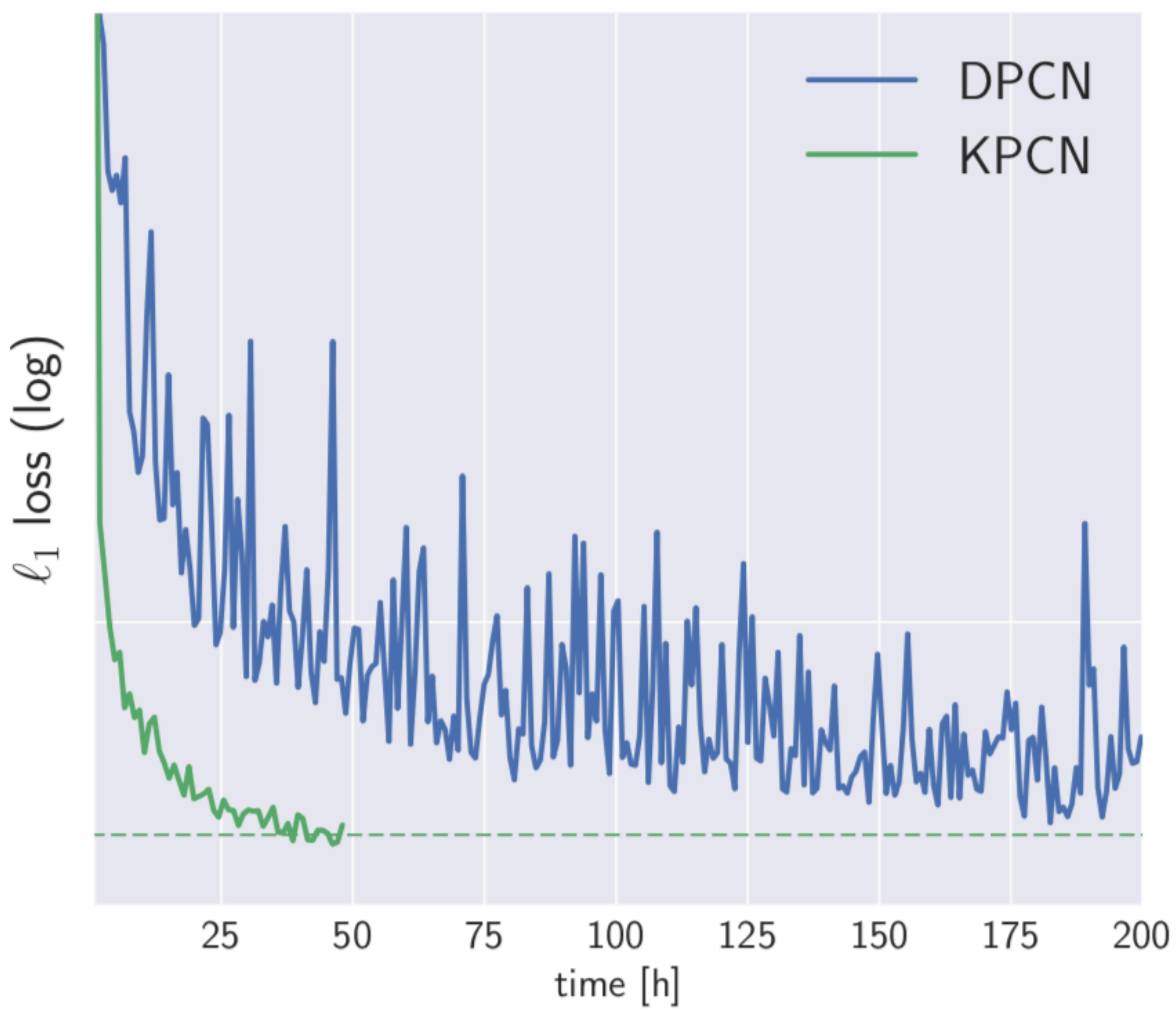
8-hidden layers used with 100 kernels of 5x5 in each layer for each network

For KPCN (kernel-predicting network), output kernel size used = 21

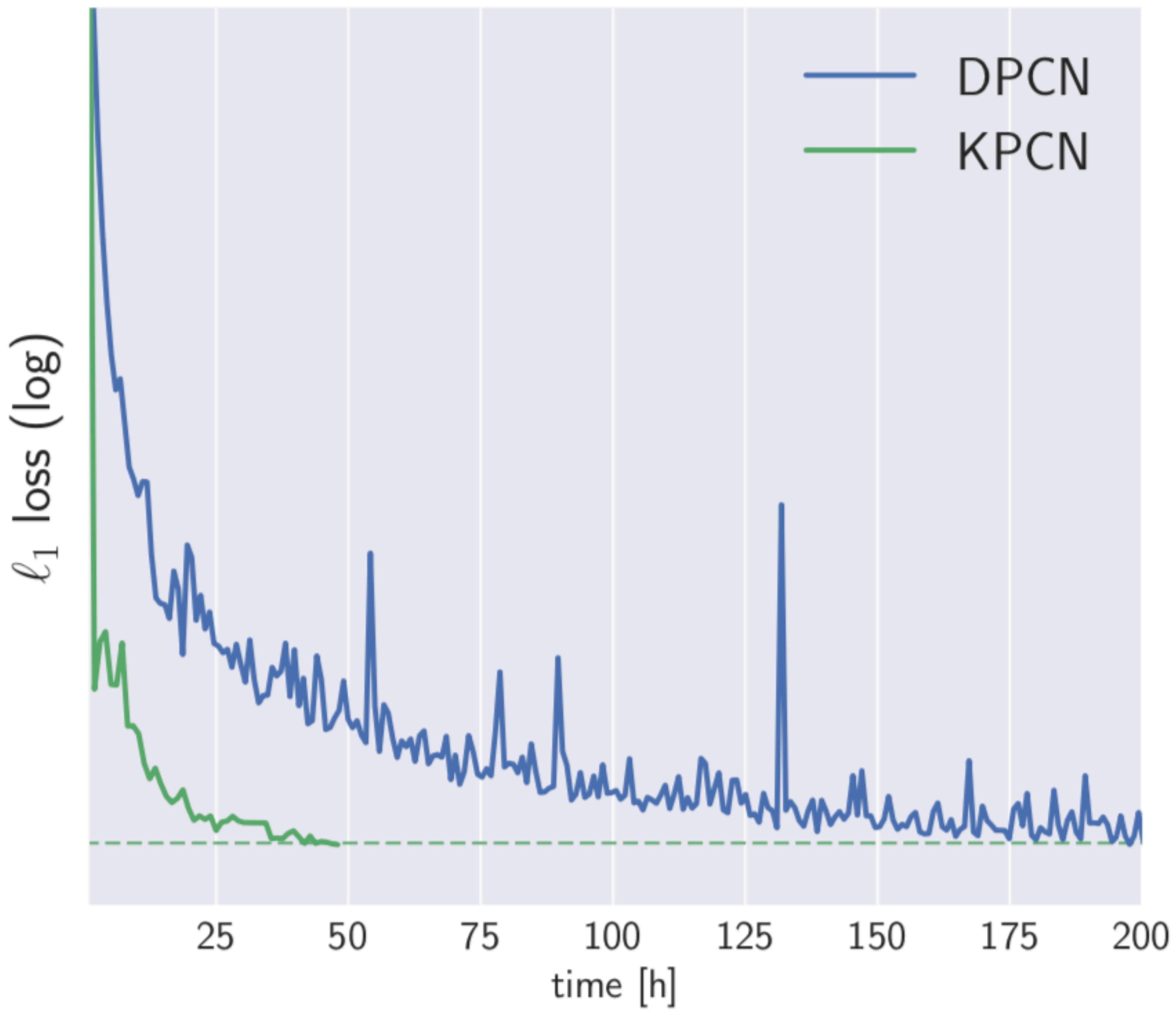
Weights for 128 app and 32 spp networks were initialized using Xavier method

Diffuse and specular components were independently trained with L1 loss metric

Learning rate of DPCN vs. KPCN



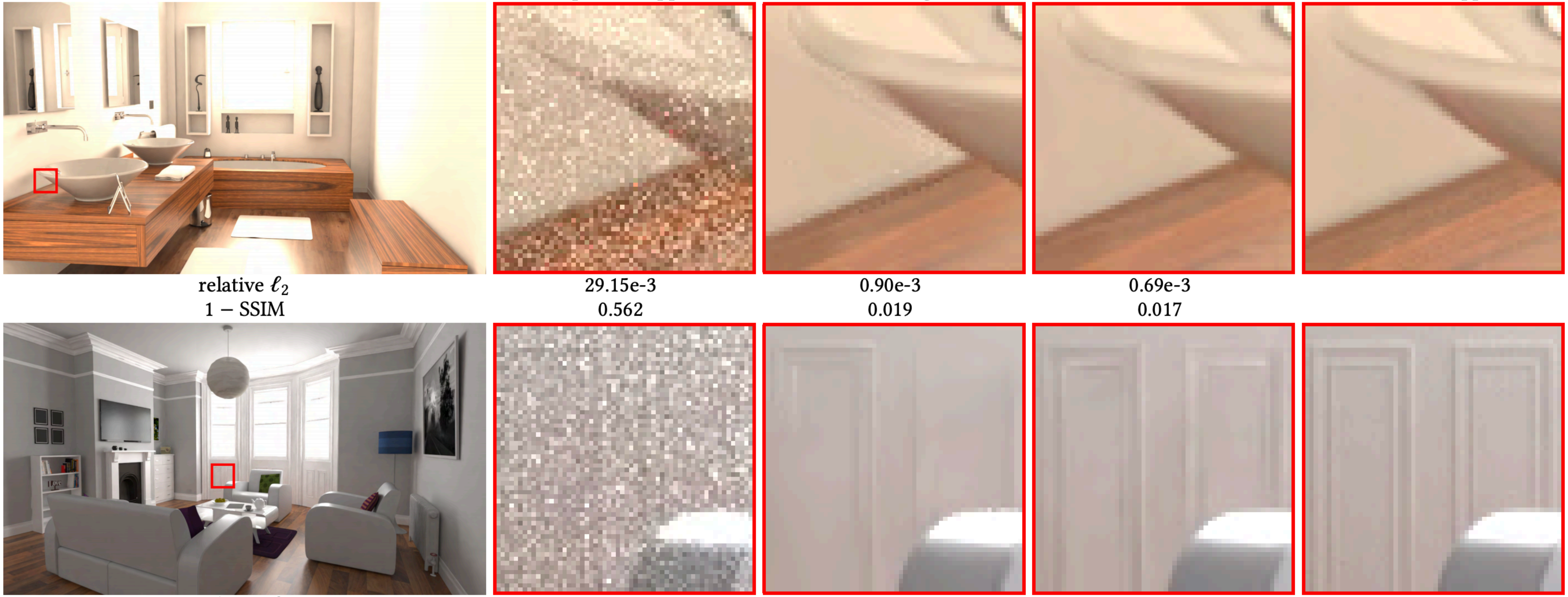
(a) Diffuse



(b) Specular

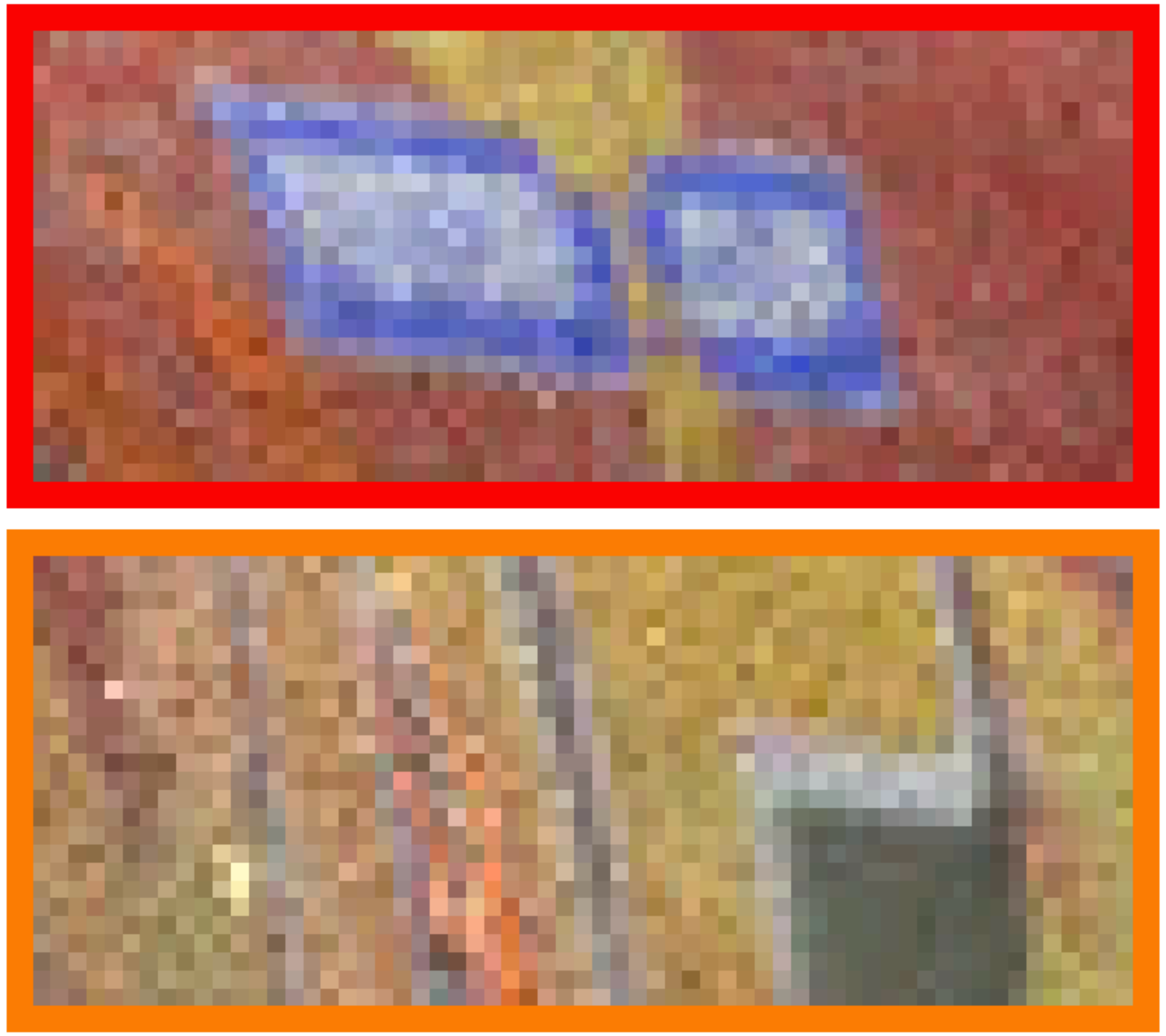
On Cars 3 dataset, KPCN converges 5-6x faster

Results



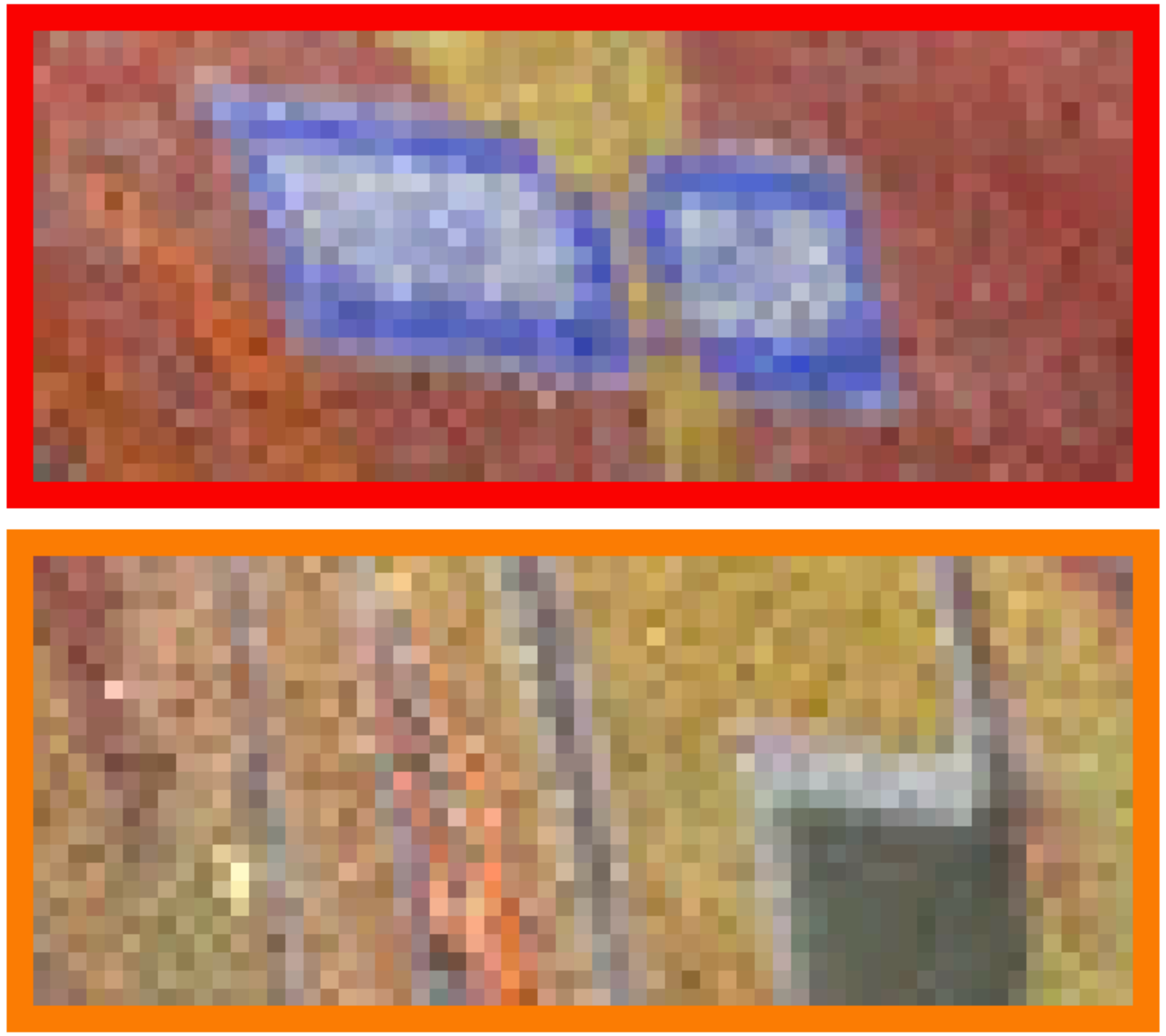
	Ours	Input (128 spp)	NFOR (log)	Ours	Ref. (32K spp)
Row 1	relative ℓ_2	29.15e-3	0.90e-3	0.69e-3	
	$1 - \text{SSIM}$	0.562	0.019	0.017	
Row 2	relative ℓ_2	38.57e-3	1.12e-3	0.92e-3	
	$1 - \text{SSIM}$	0.552	0.025	0.024	

Ablation study



Input (32 spp)

Ablation study



Input (32 spp)

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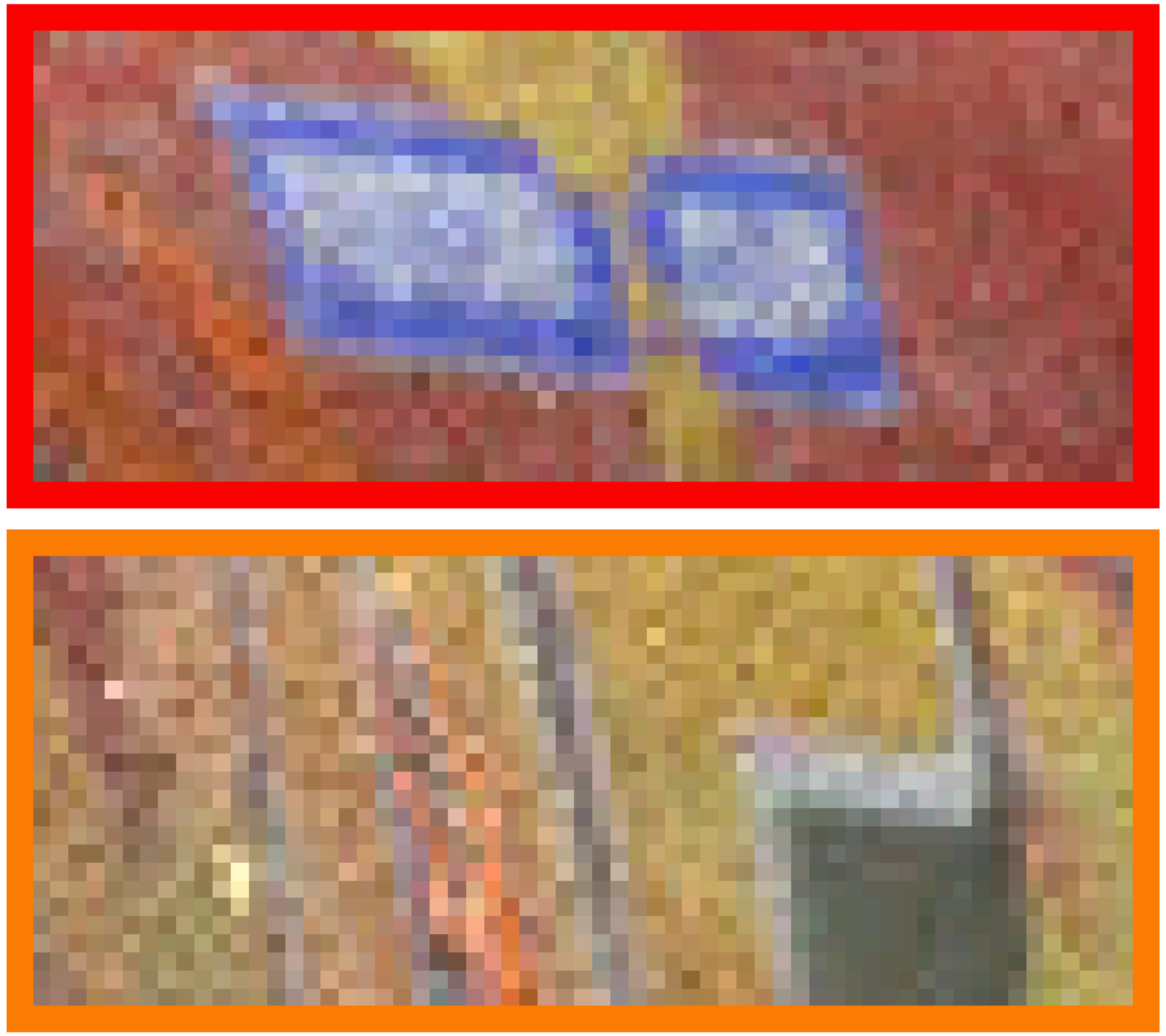


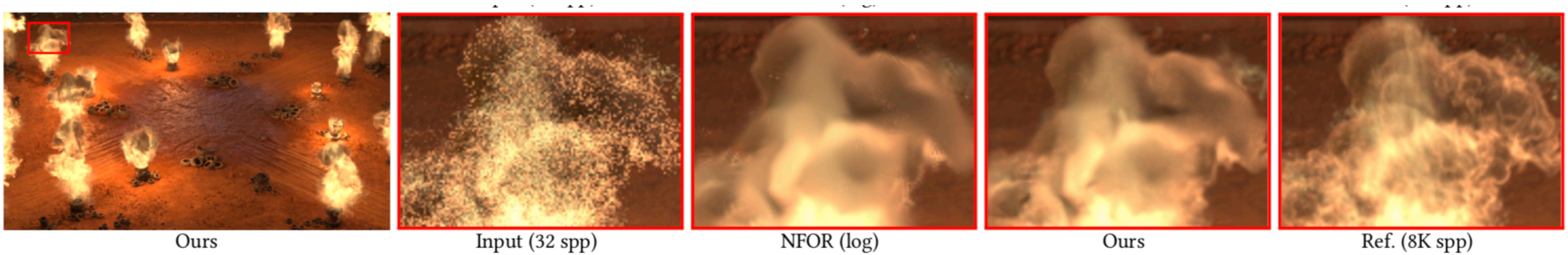
Input (32 spp)

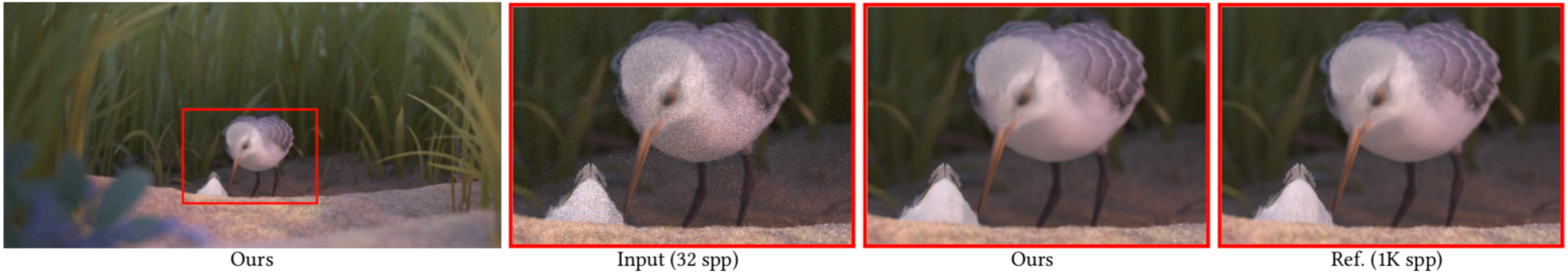
w/o Decomposition,
w/o Albedo divide

Ablation study

w/o Decomposition, w/o Albedo divide | w/ Decomposition, w/o Albedo divide | w/o Decomposition, w/ Albedo divide | w/ Decomposition, w/ Albedo divide | Ref. (2K spp)

Ablation study



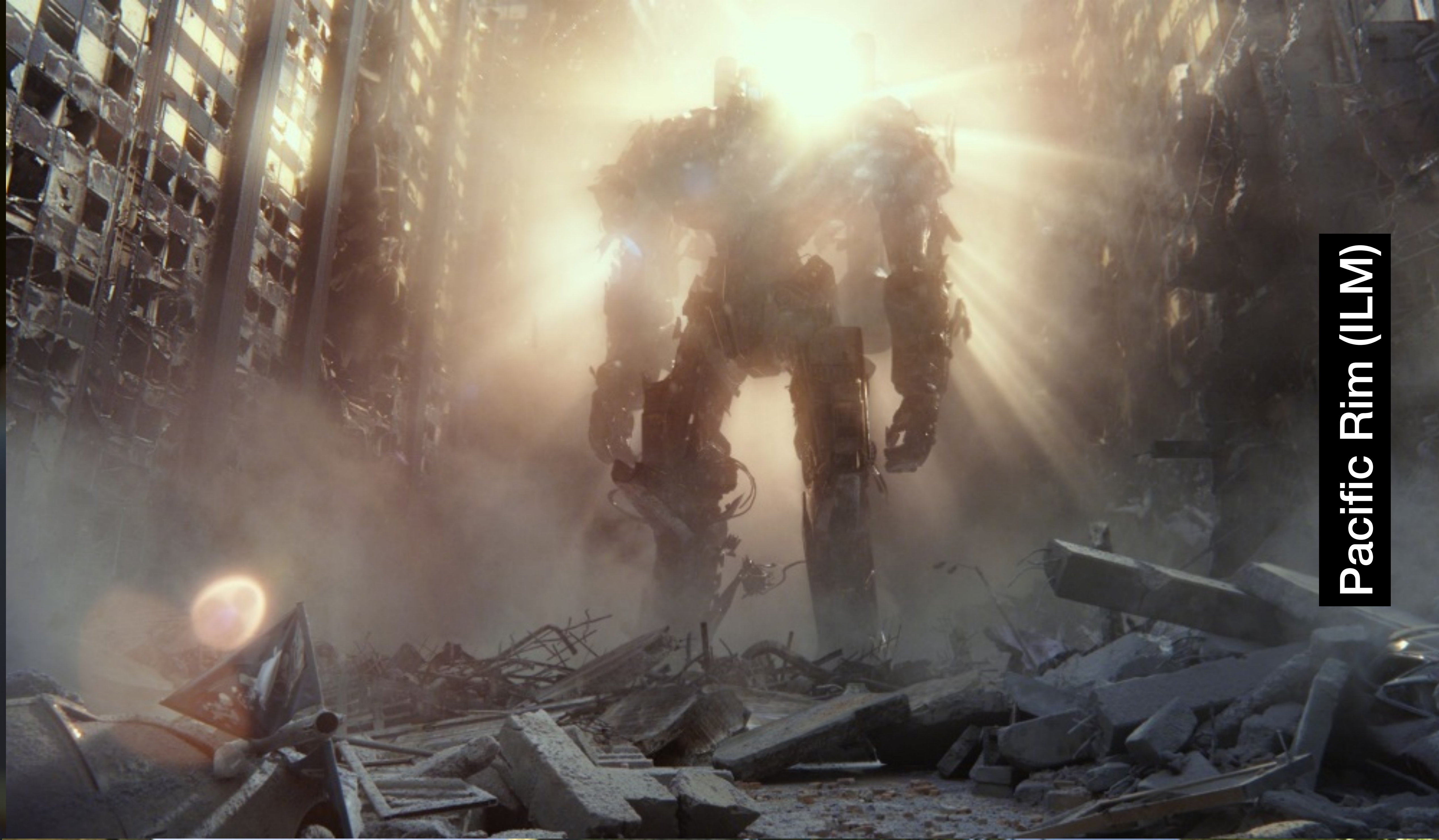


Also works on Piper short movie frames

Interactive Reconstruction of Monte Carlo Sequences

Chaitanya et al. [2017]


Toy Story (Pixar)


Pacific Rim (ILM)


Crisis 3 (Crytek)

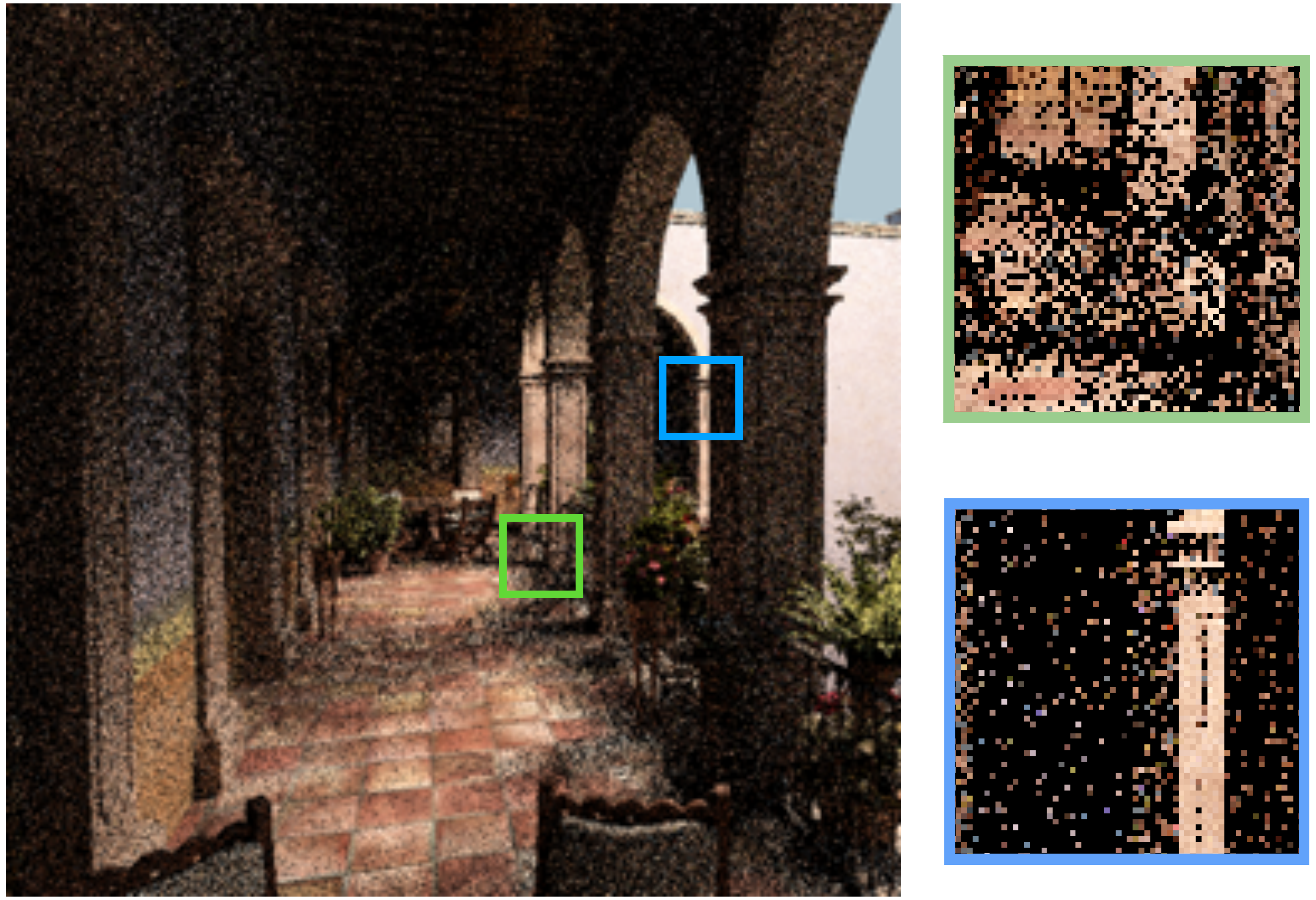

Halo 3 (Bungie)

Motivation: Interactive Reconstruction

Limited to a few rays per pixel @ 1080p @ 30Hz

Never enough to reconstruct an image

Deep learning approach for interactive graphics



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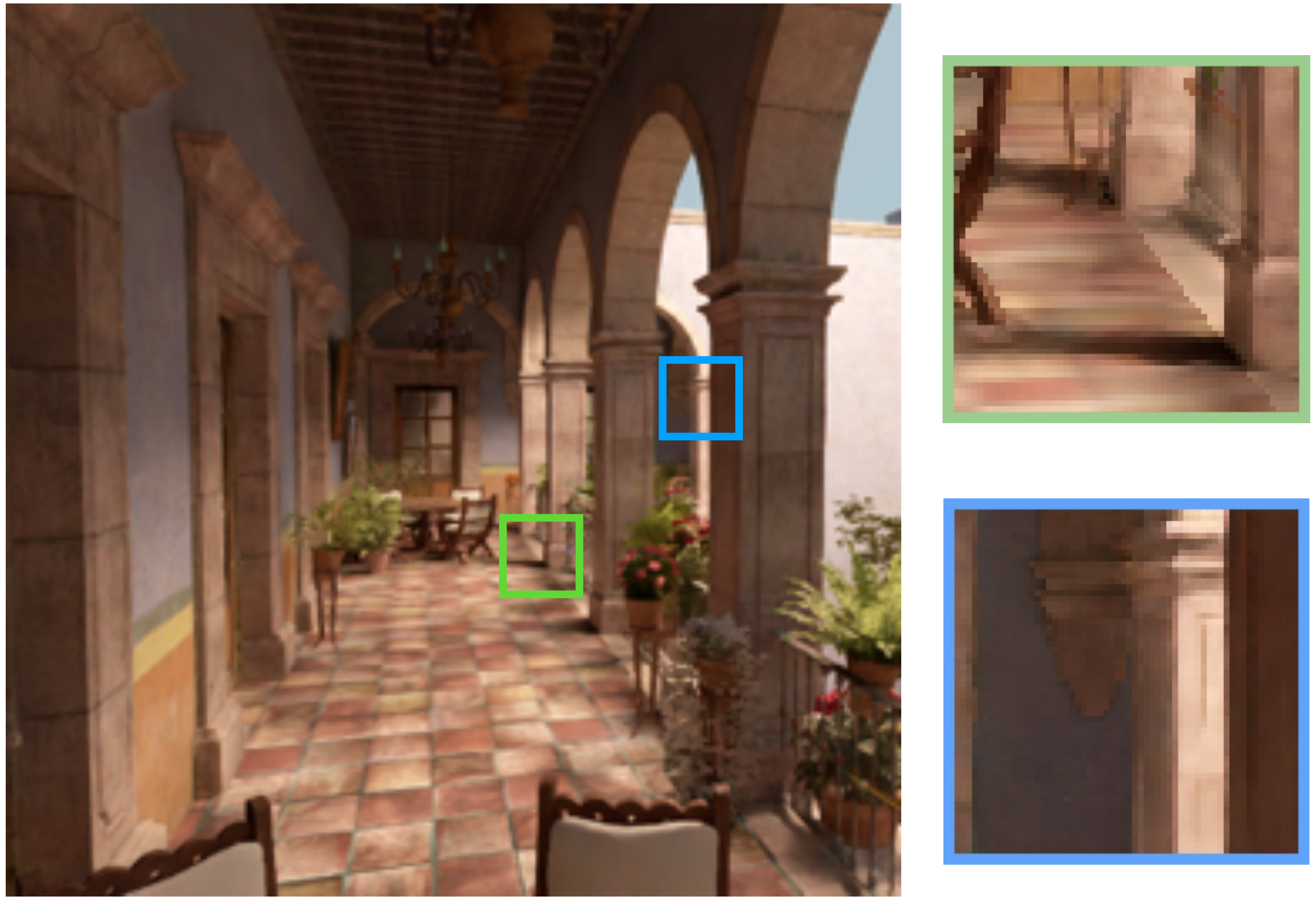
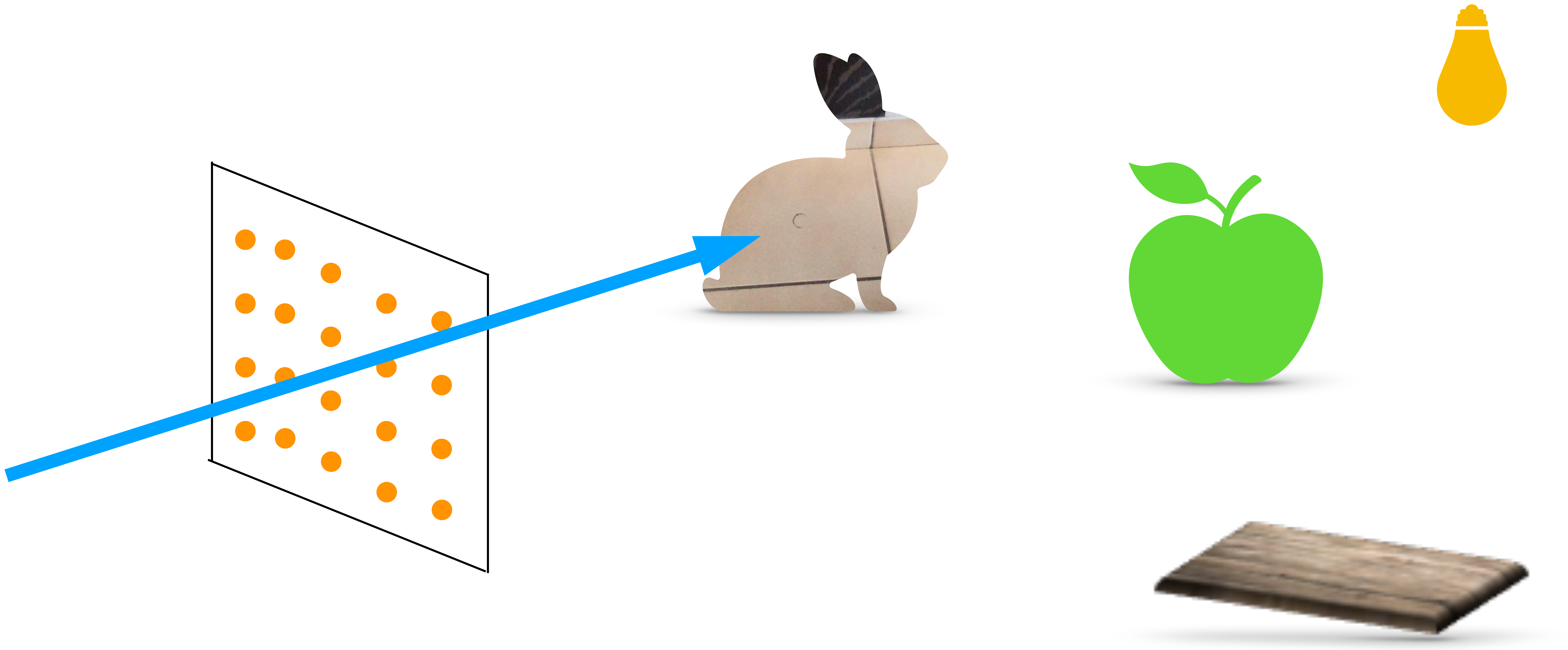


Problem Statement

Handle generic effects:

- Soft shadows
- Diffuse and specular reflections
- Global illumination (one-bounce)
- No Motion blur or depth of field

System setup: Path tracing



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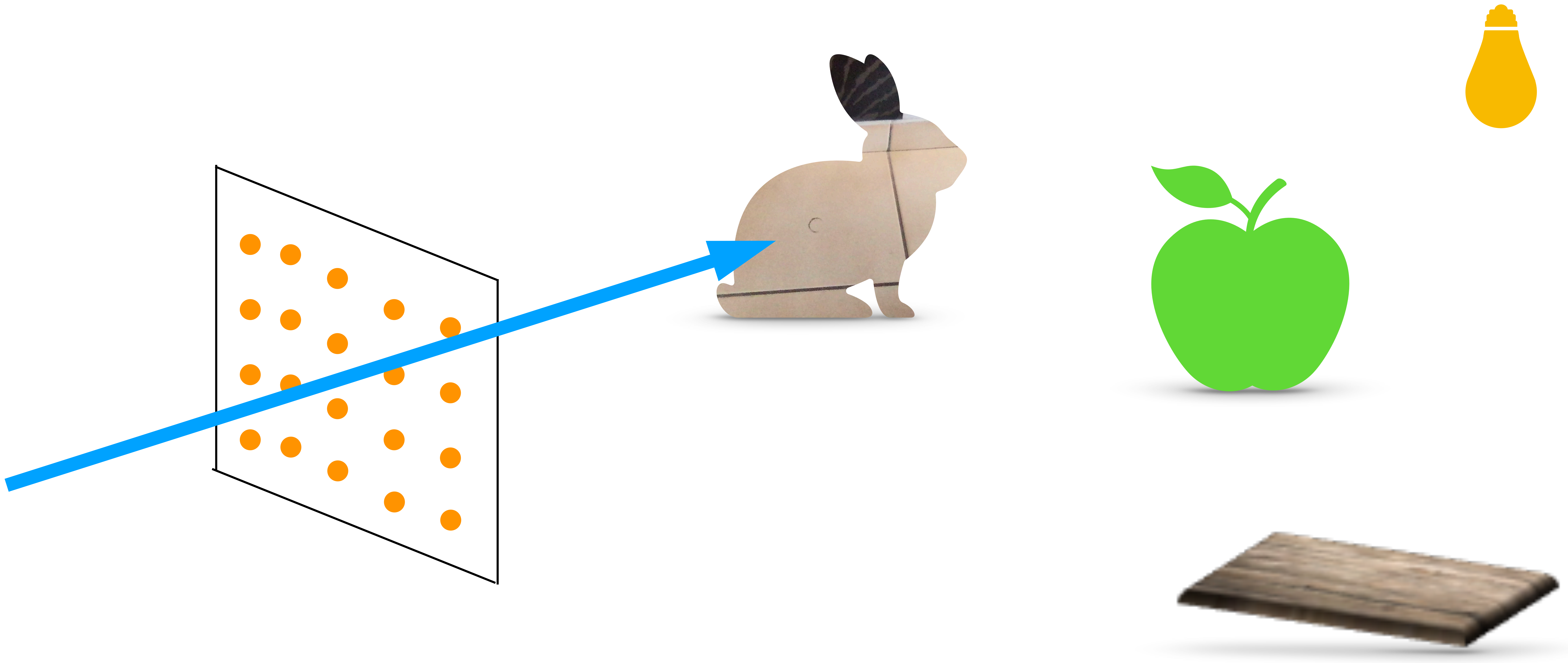

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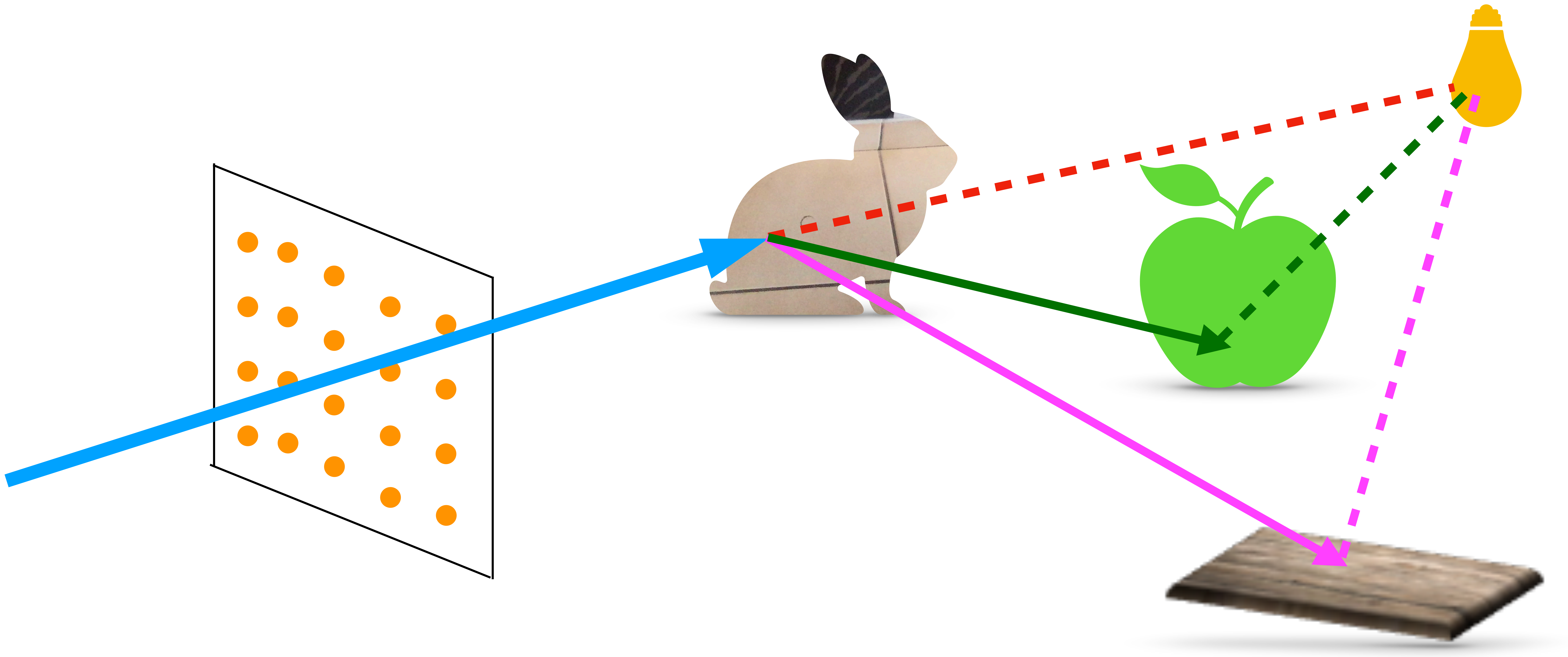

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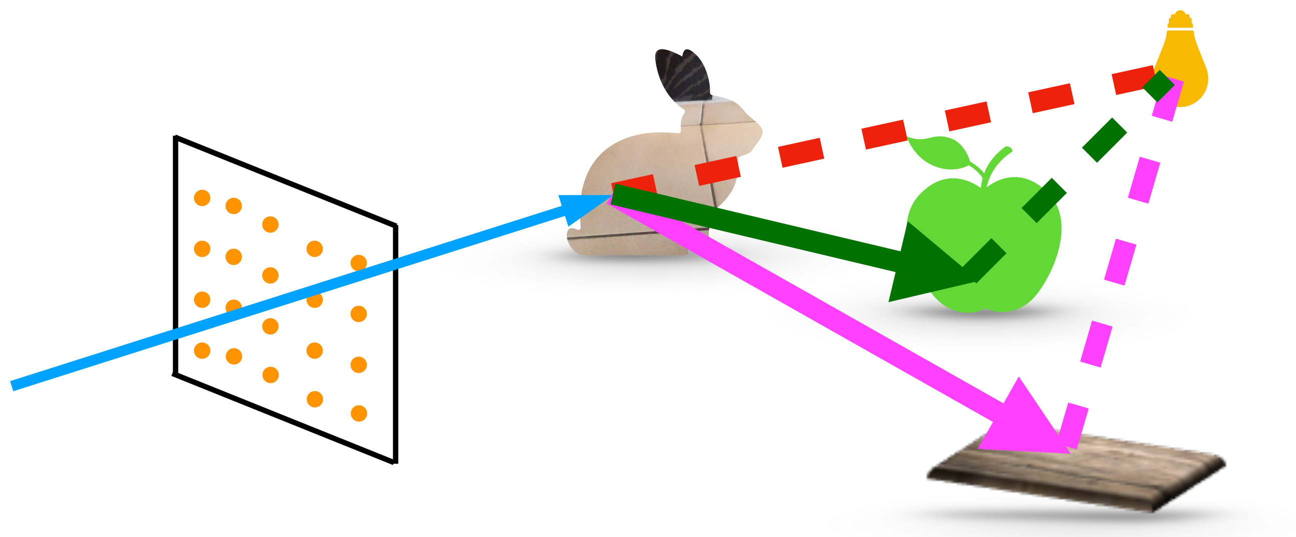


Rasterize primary hits in G-buffers

Path-tracing from the primary paths

- 1 ray for direct shadows
- 2 rays for indirect (sample + connect)

1 direct + 1 indirect path (spp)

Denoising Autoencoder (DAE)

Recurrent Autoencoder

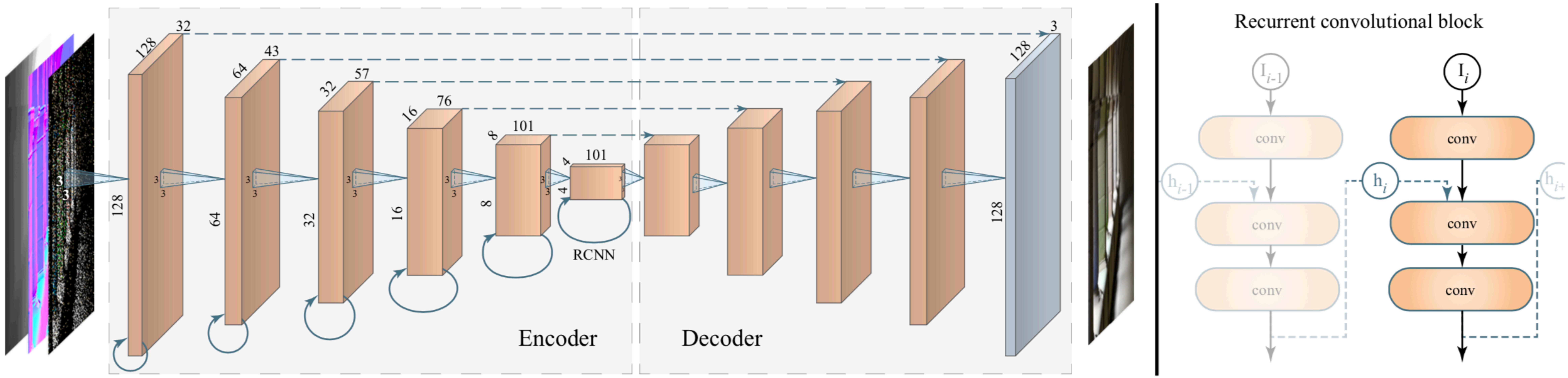


Fig. 2. Architecture of our recurrent autoencoder. The input is 7 scalar values per pixel (noisy RGB, normal vector, depth, roughness). Each encoder stage has a convolution and 2×2 max pooling. A decoder stage applies a 2×2 nearest neighbor upsampling, concatenates the per-pixel feature maps from a skip connection (the spatial resolutions agree), and applies two sets of convolution and pooling. All convolutions have a 3×3-pixel spatial support. On the right we visualize the internal structure of the recurrent RCNN connections. I is the new input and h refers to the hidden, recurrent state that persists between animation frames.

[Chaitanya et al. 2017]

Recurrent Neural Networks

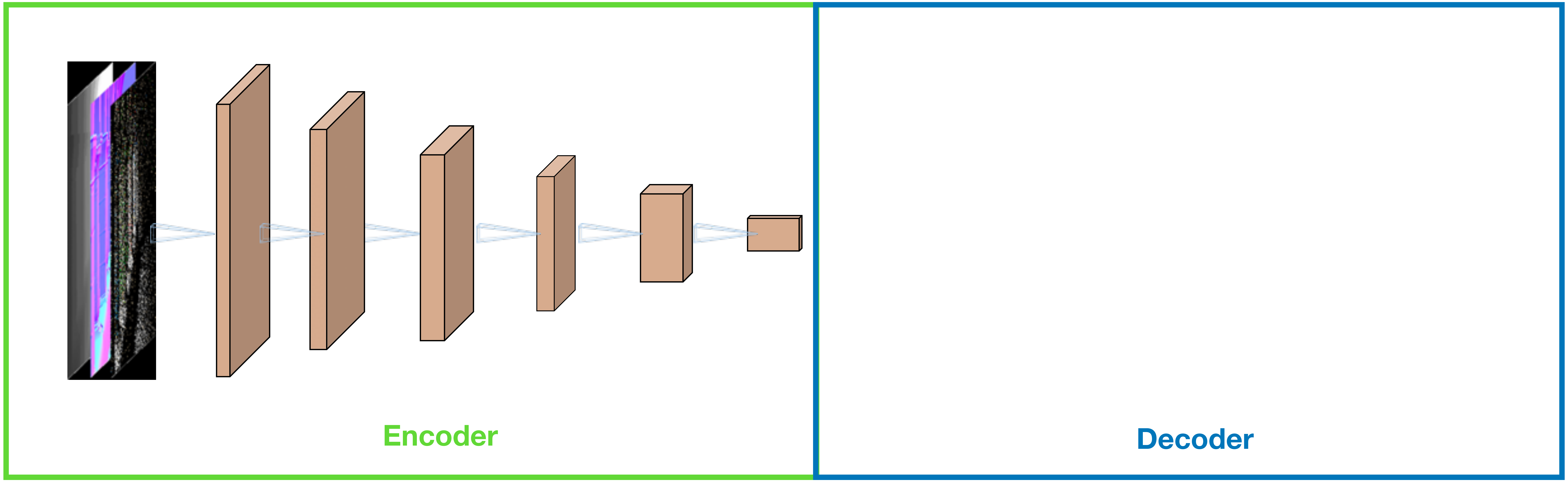
Encoder and decoder stages for dimensionality reduction

Encoder

Decoder

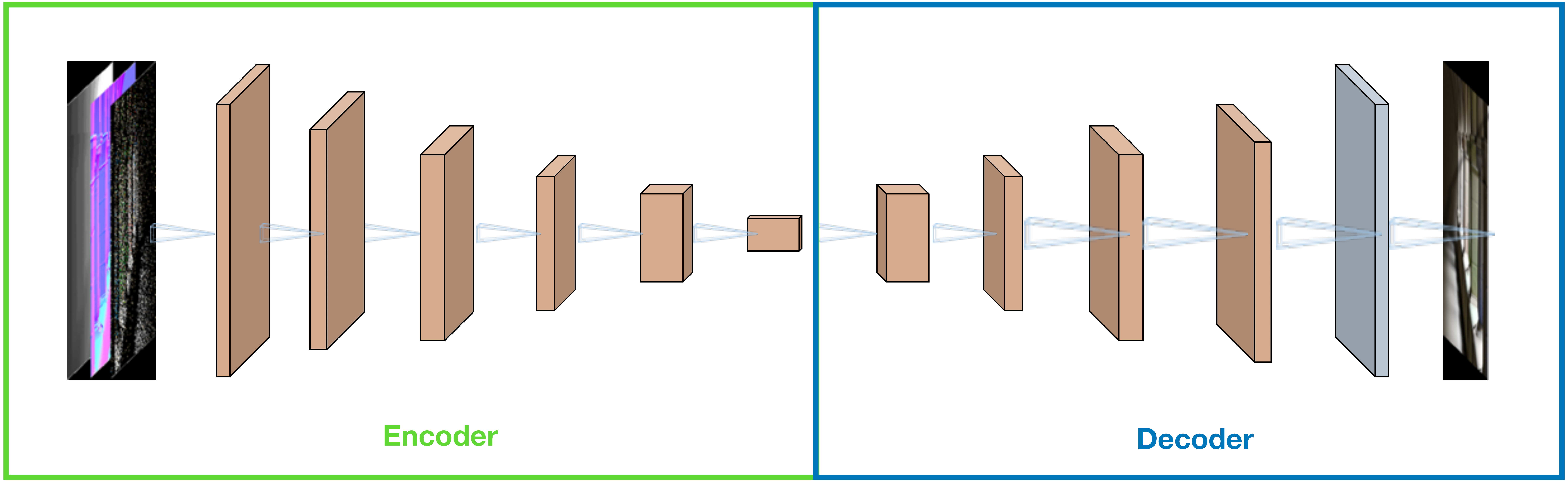
Recurrent Neural Networks

Encoder and decoder stages for dimensionality reduction



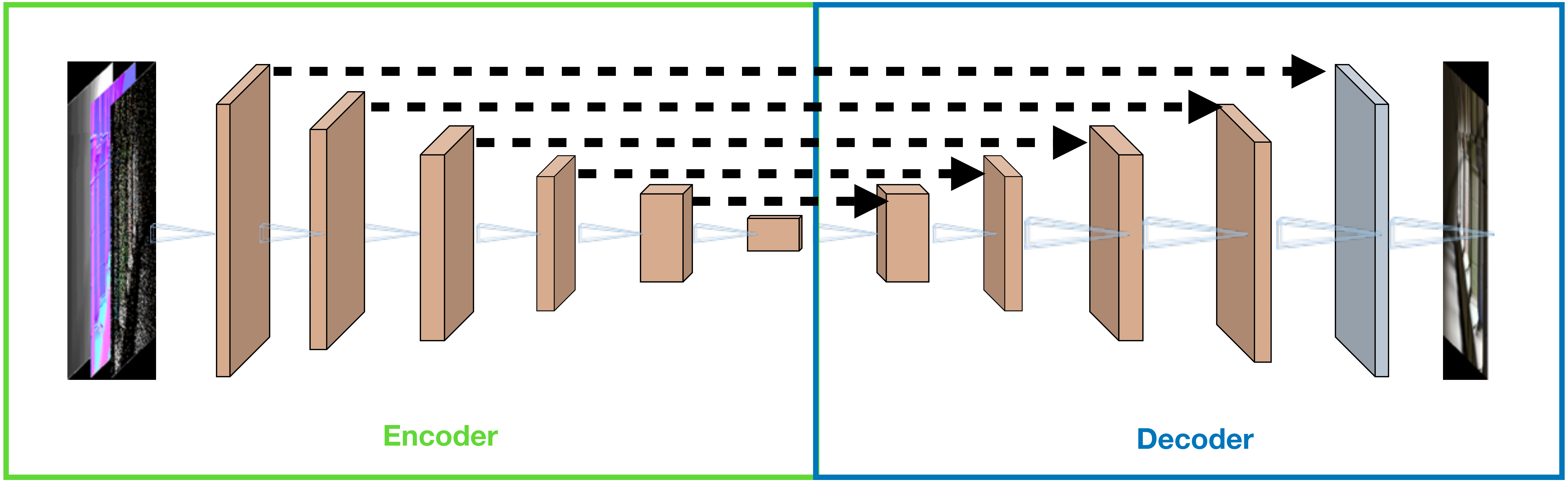
Recurrent Neural Networks

Encoder and decoder stages for dimensionality reduction



Recurrent Neural Networks

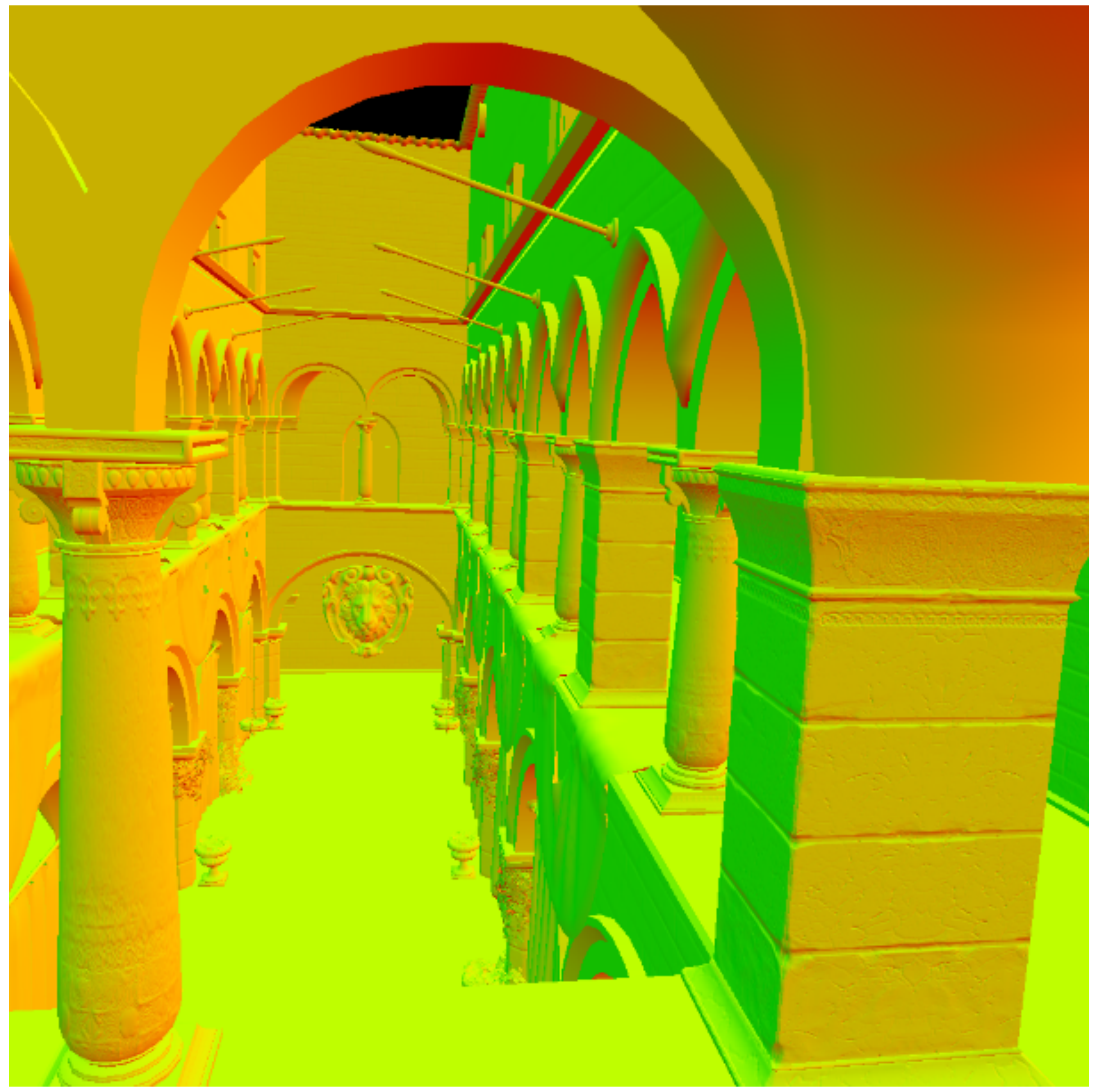
Encoder and decoder stages for dimensionality reduction



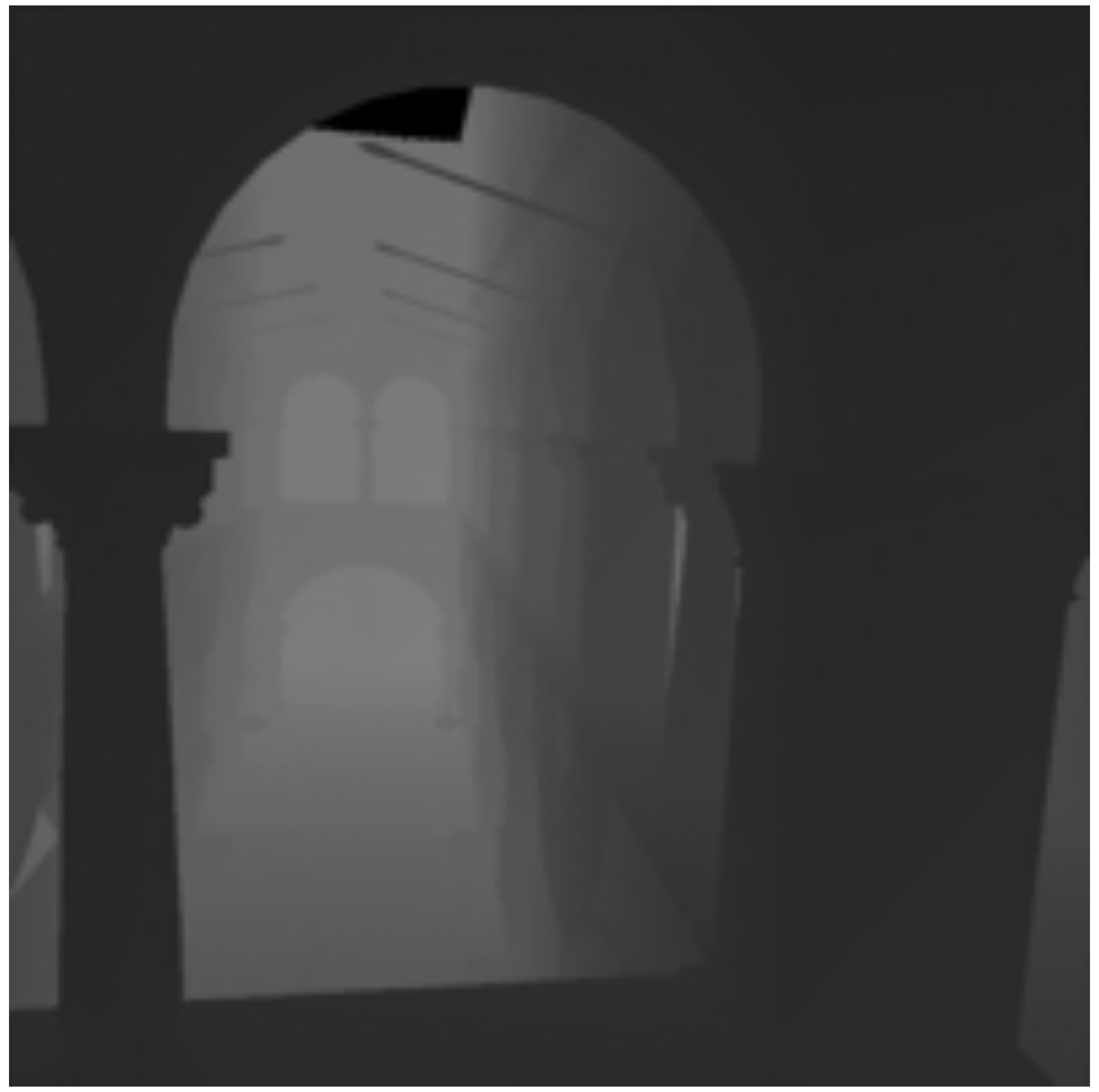
Skip connections to reintroduce lost information

Auxillary Features

Untextured color



View space normals



Linearize depth

Training sequences

SponzaDiffuse

SponzaGlossy

Classroom

Training sequences

SponzaDiffuse

SponzaGlossy

Classroom

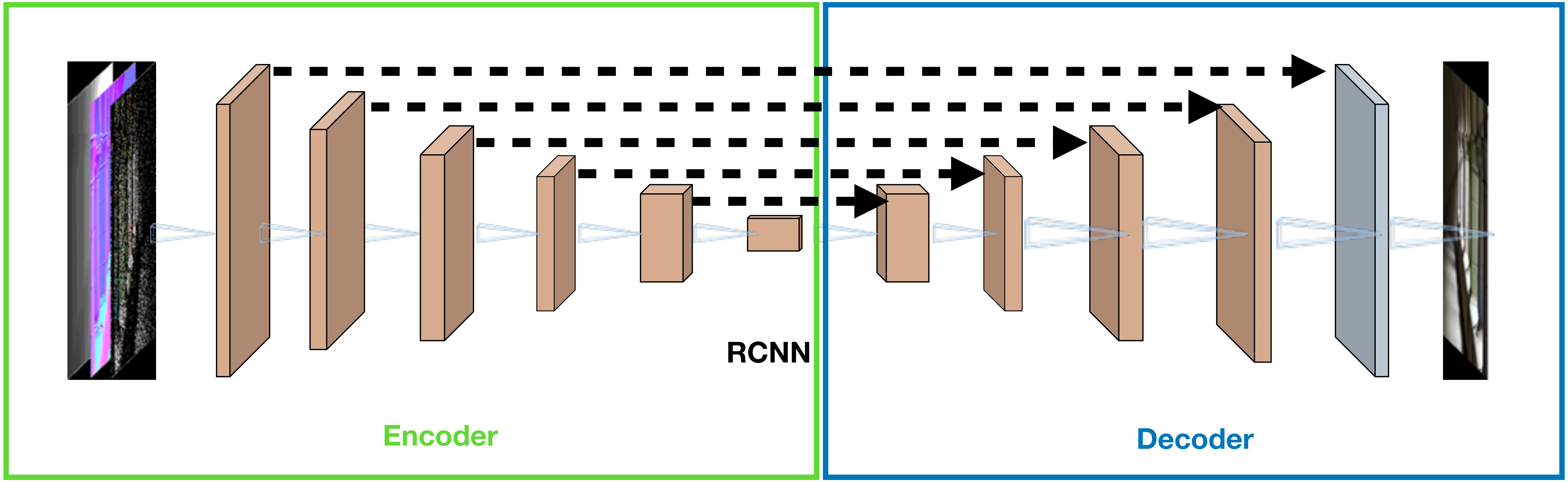

1spp approx. 70 ms


DAE 1spp
approx. 70 ms + approx. 60 ms


Reference 1024 spp
approx. 240 ms

Recurrent Denoising Autoencoder

Feedback loops to retain important information after every encoding stage



Recurrent Denoising Autoencoder

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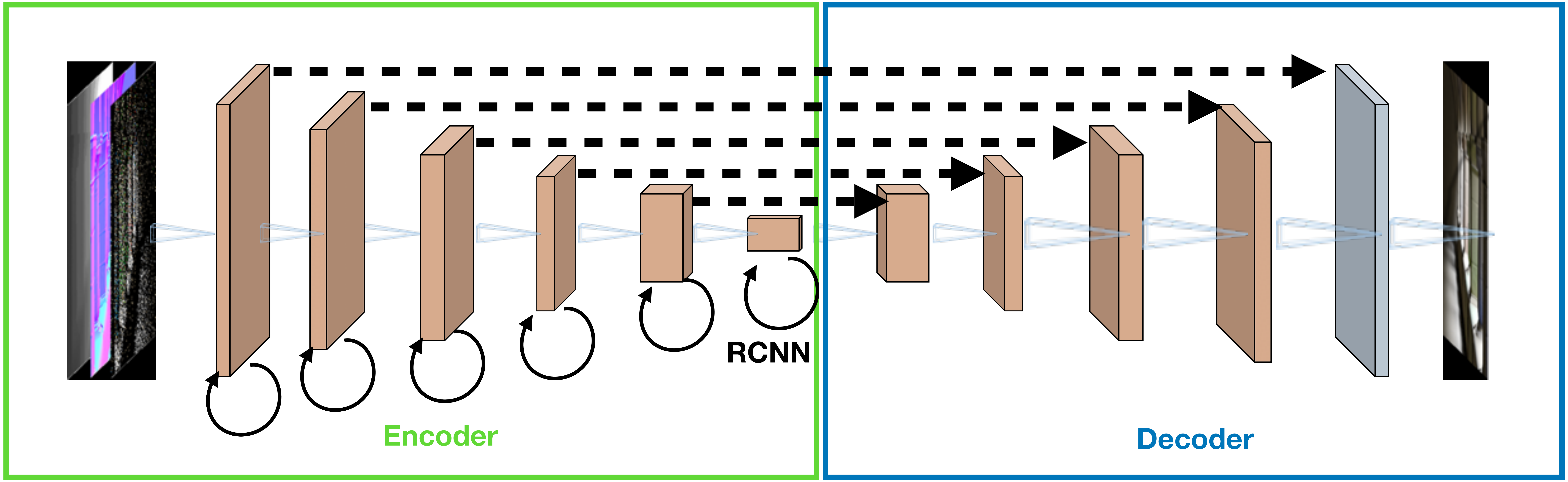
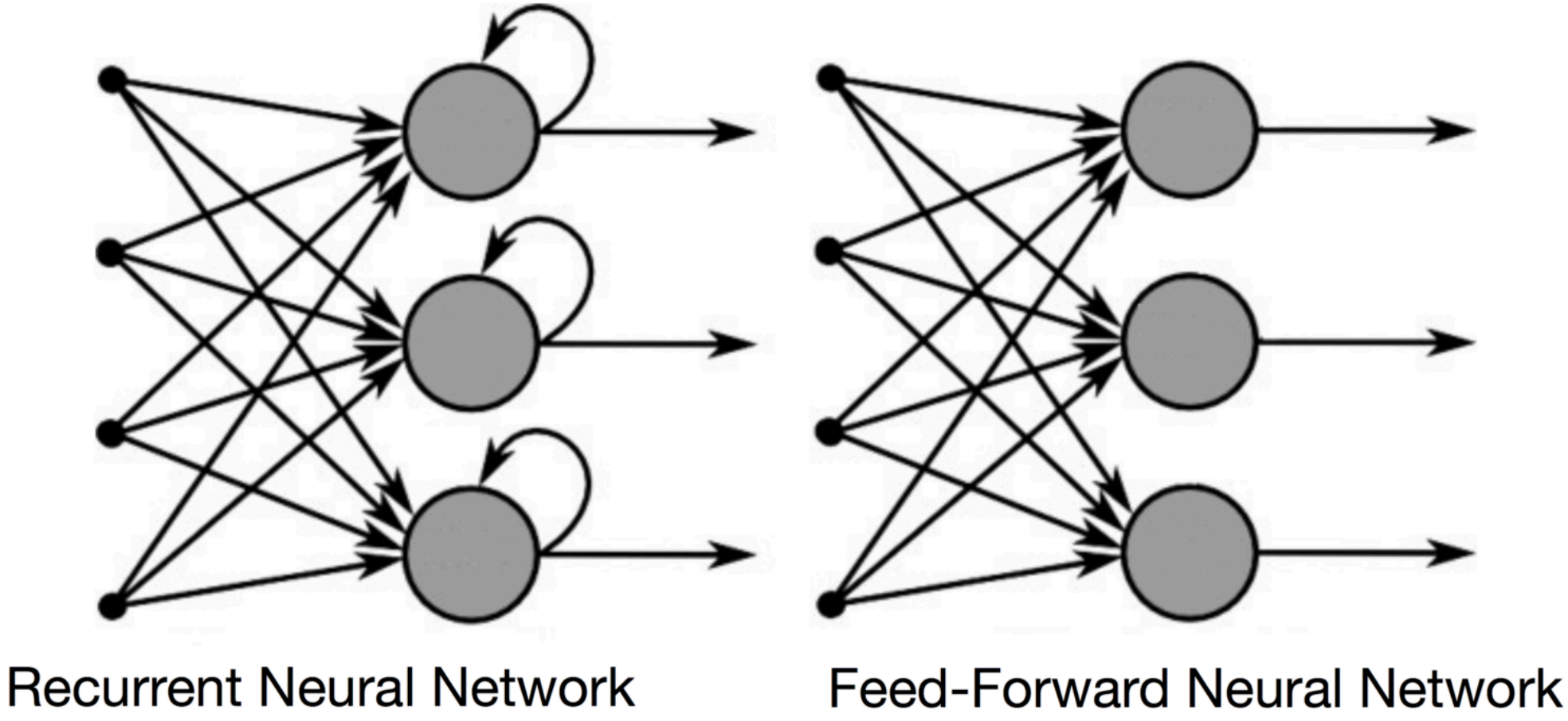


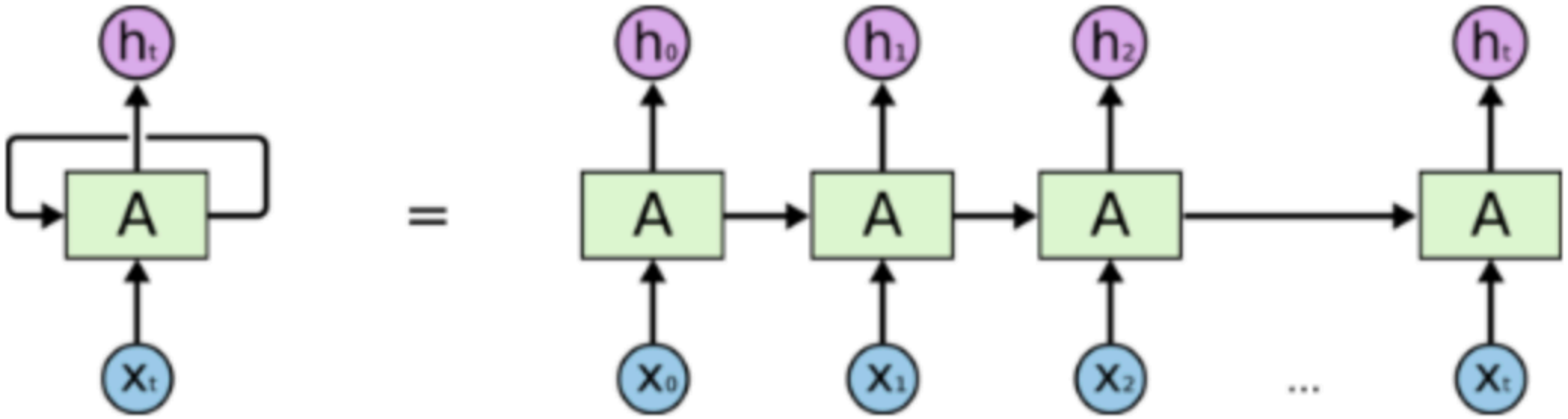
Recurrent Neural Networks vs. Simple Feed-Forward NN

Source link



Recurrent Neural Networks

Source link



An unrolled recurrent neural network.

Recurrent Neural Networks

Source link

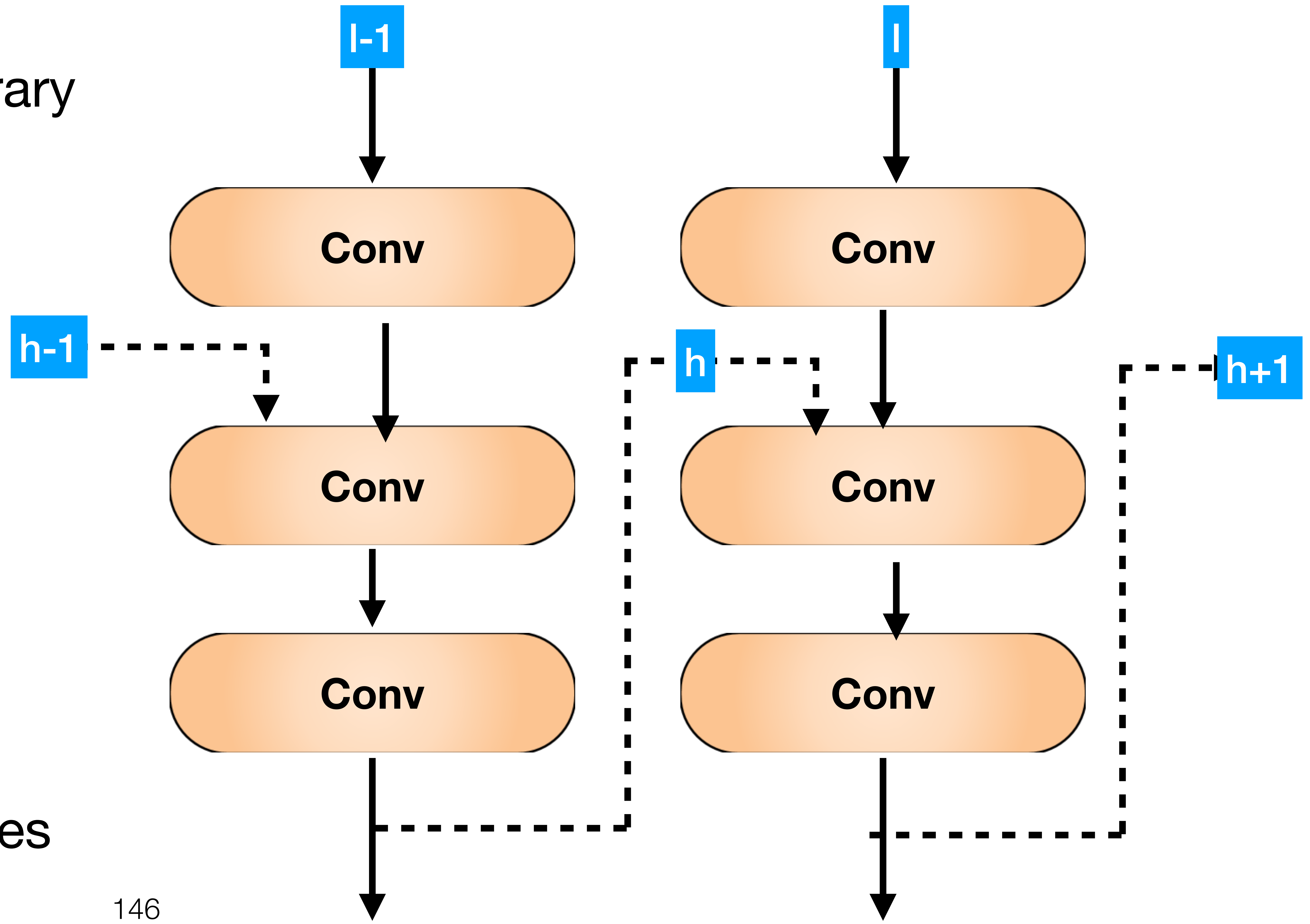
Fully convolutional blocks to support arbitrary image resolution

6 RNN blocks, one per pool layer in the encoder

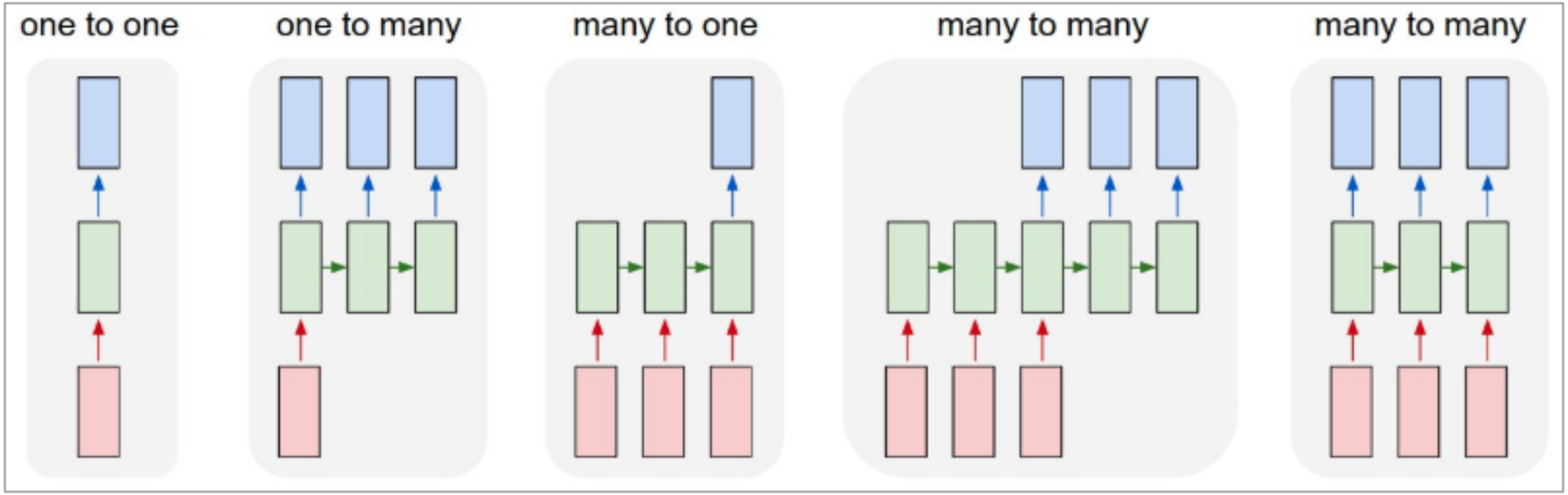
Design:

- 1 conv layer (3x3) for current features

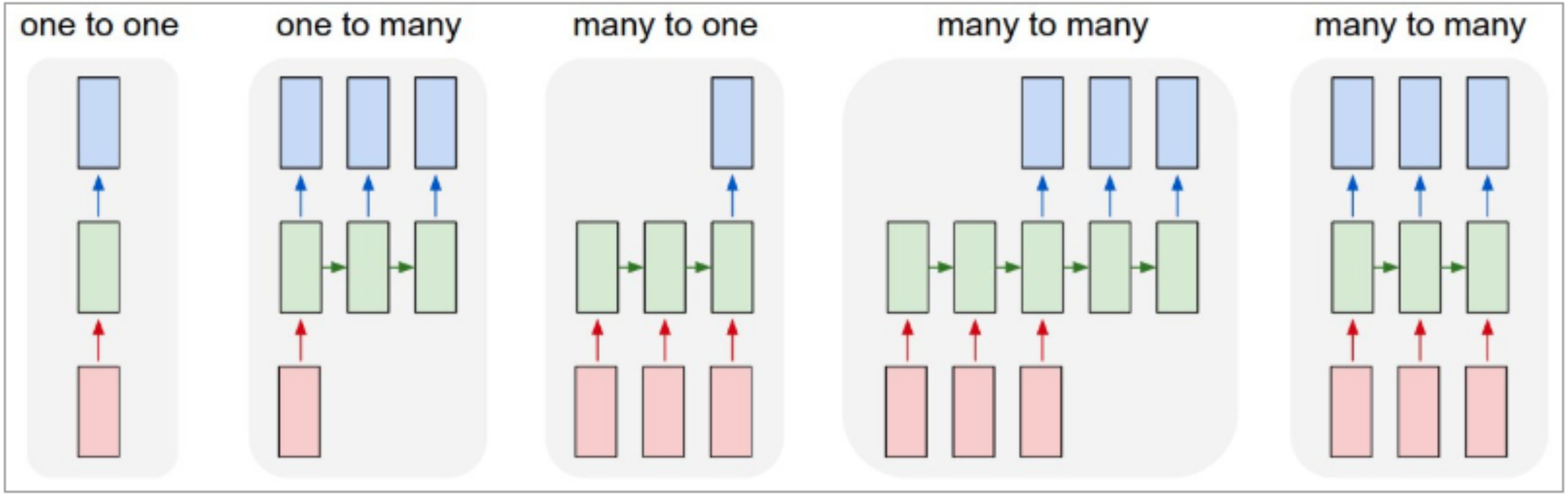
- 2 conv layers (3x3) for previous features



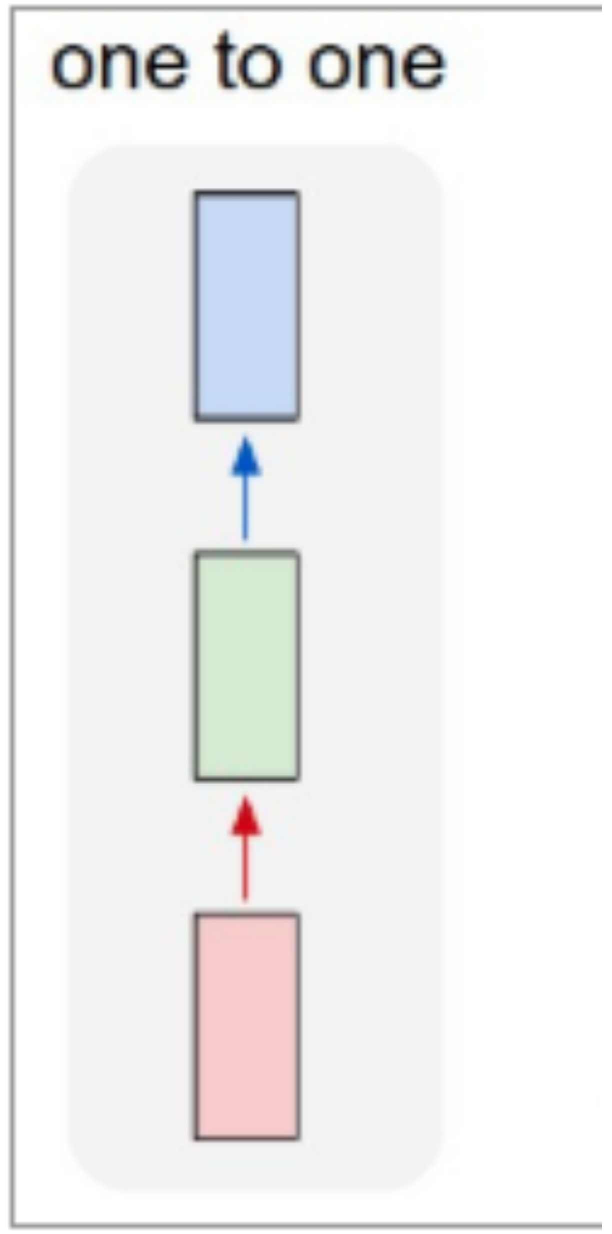
Recurrent Neural Networks



Recurrent Neural Networks

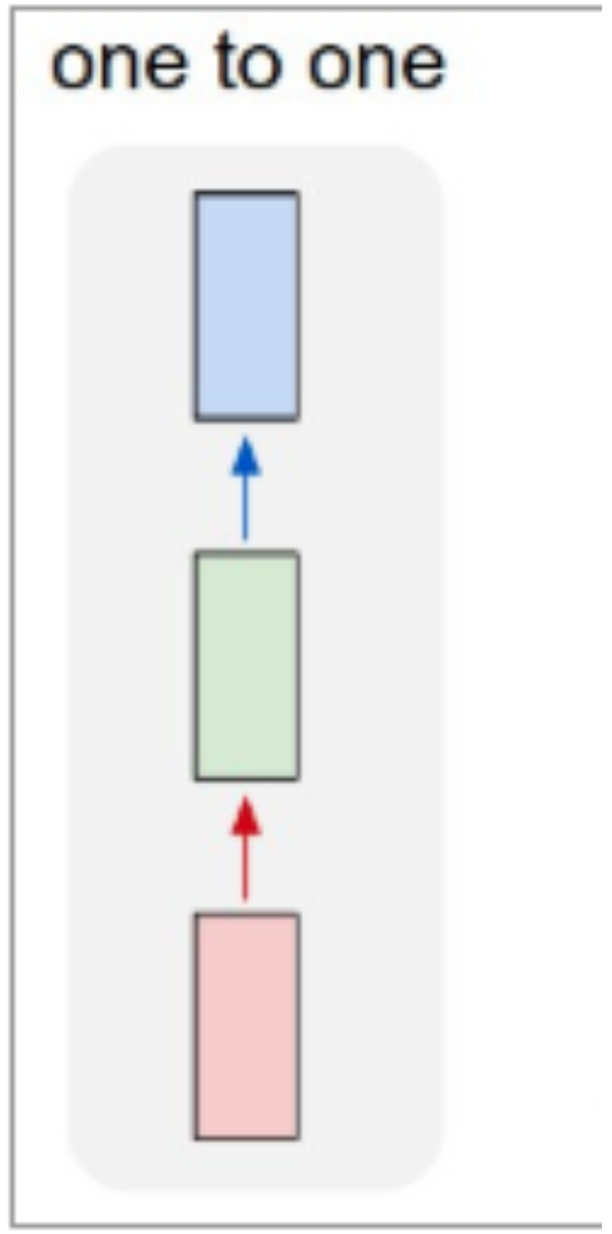


Recurrent Neural Networks



Recurrent Neural Networks

CNNs,
fixed input,
fixed output



Recurrent Neural Networks

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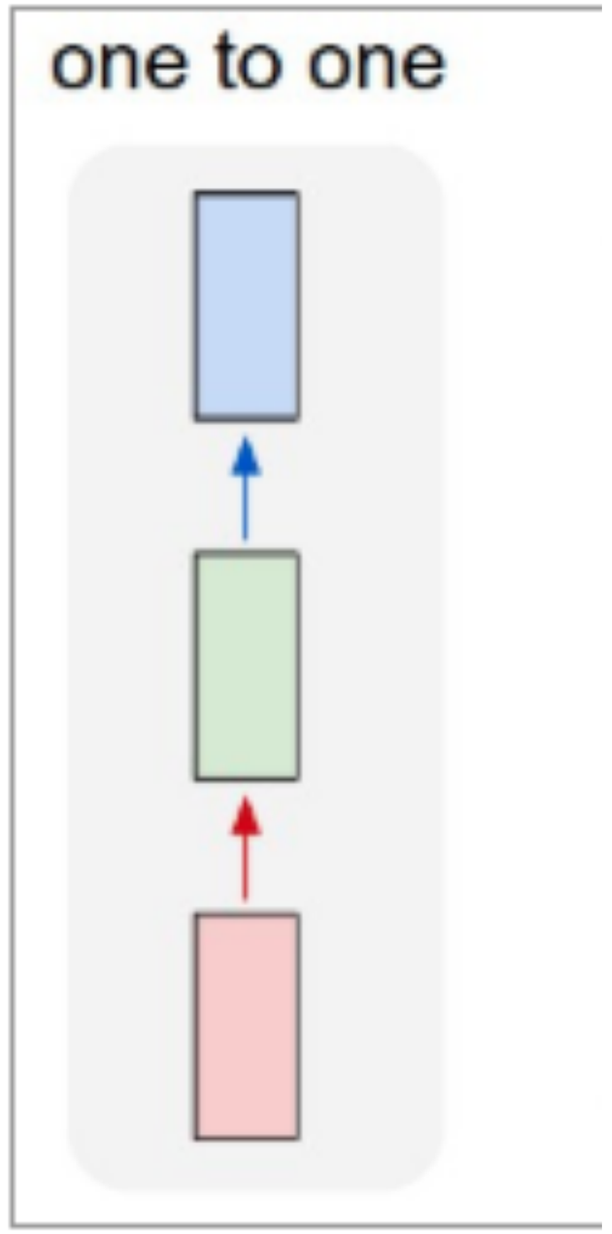

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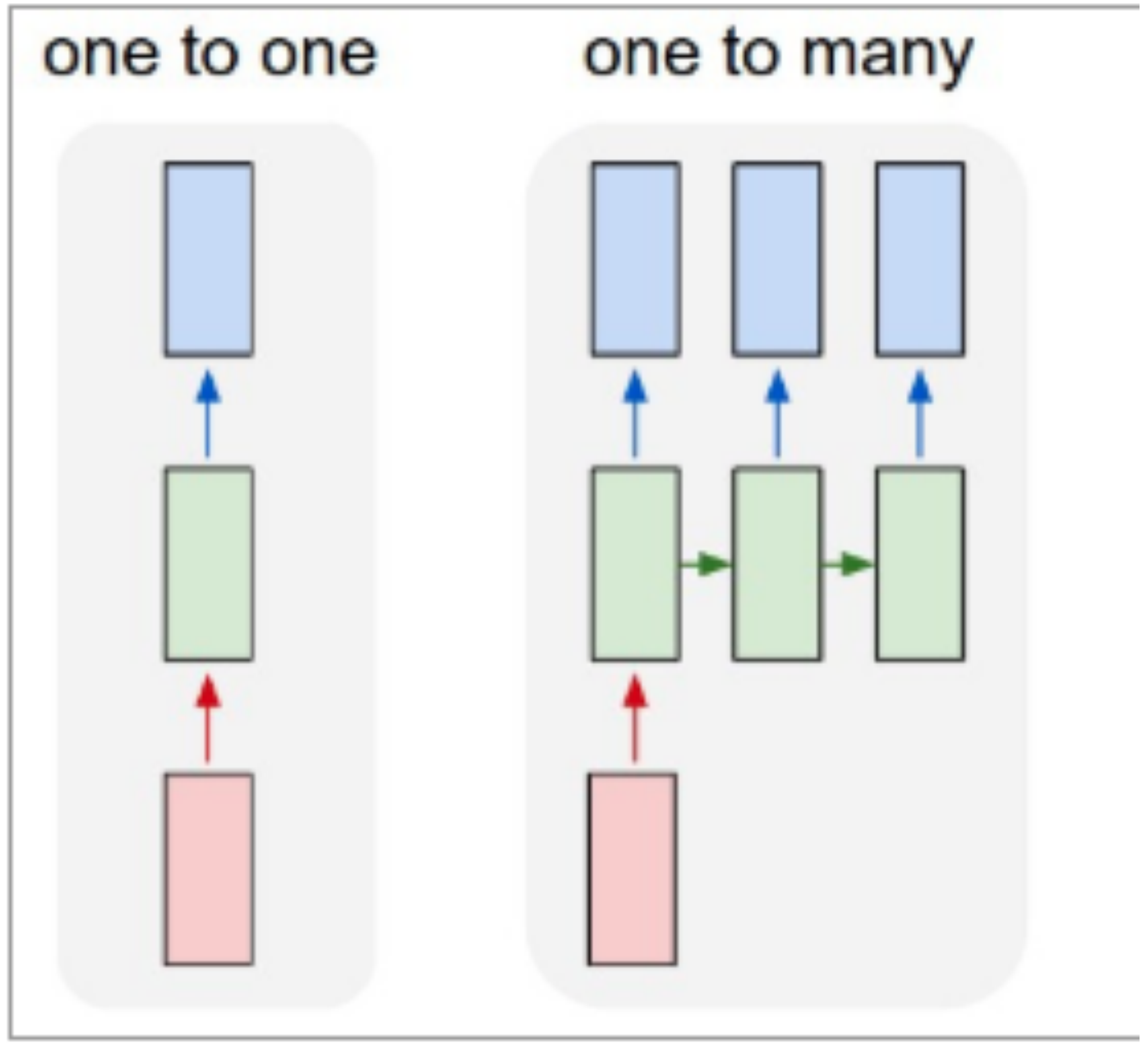

Recurrent Neural Networks

CNNs,
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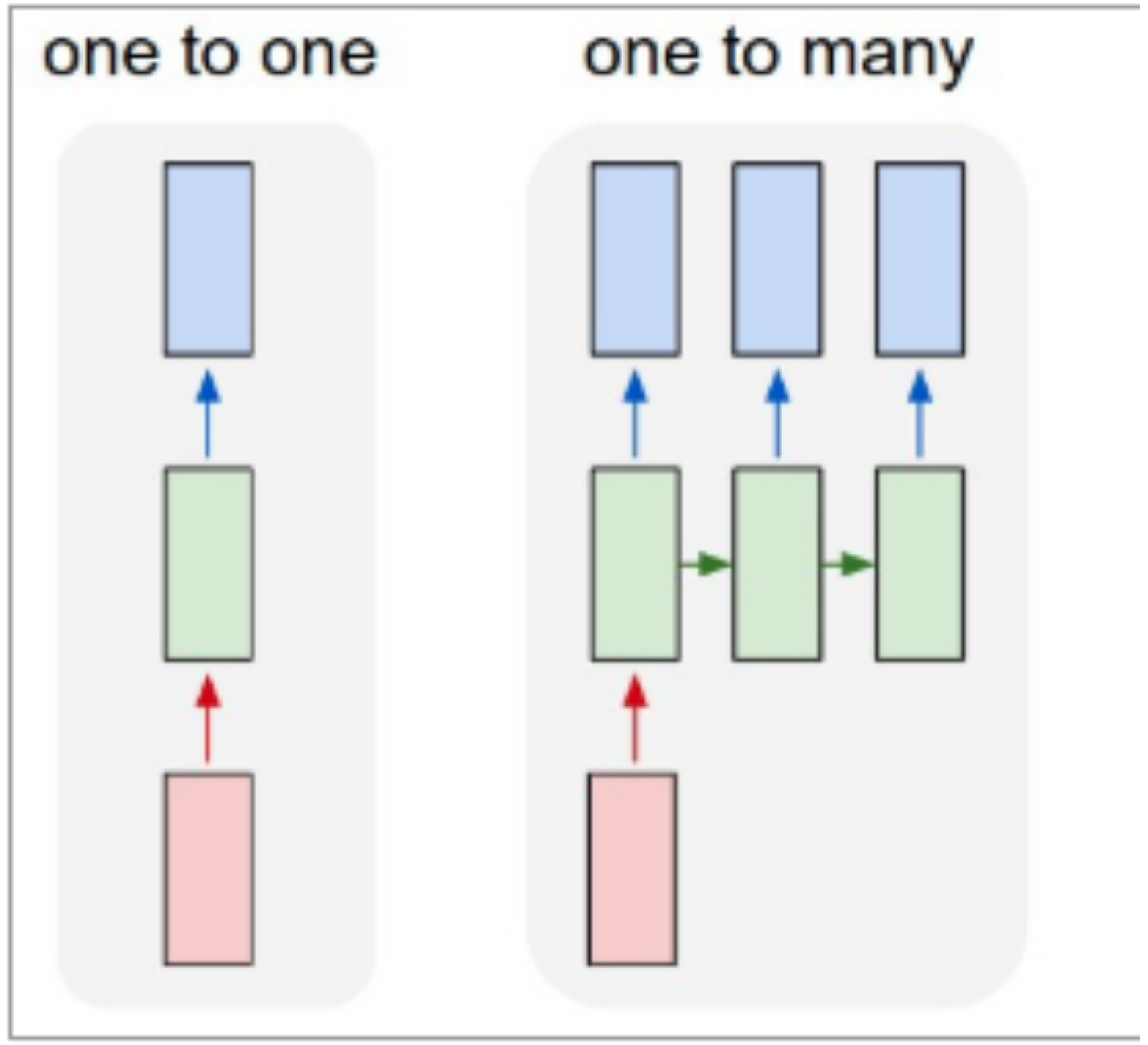


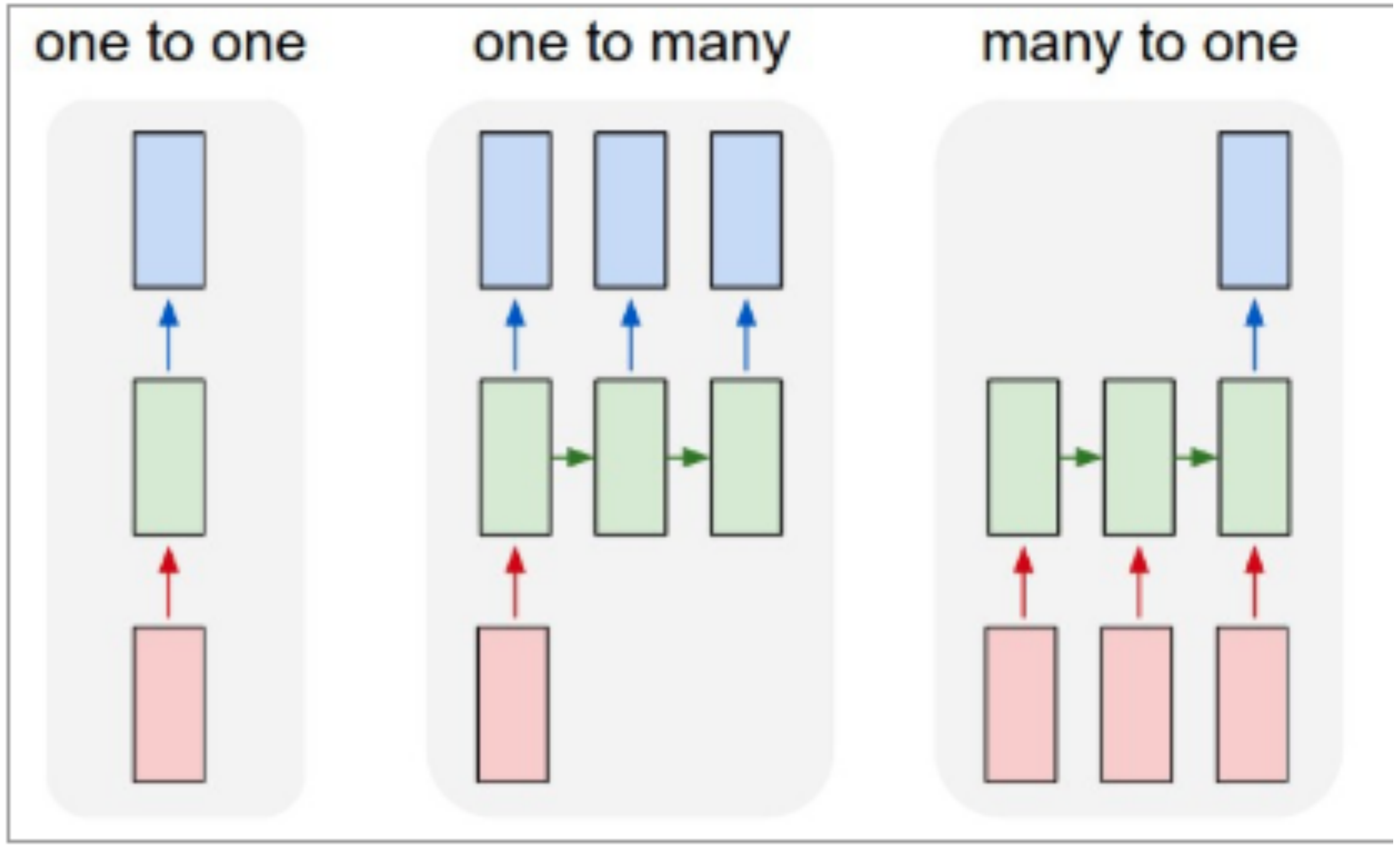
Sequence output

e.g., image captioning takes an image as input and outputs a sentence of words

Recurrent Neural Networks

CNNs,
fixed input,
fixed output

Sequence input



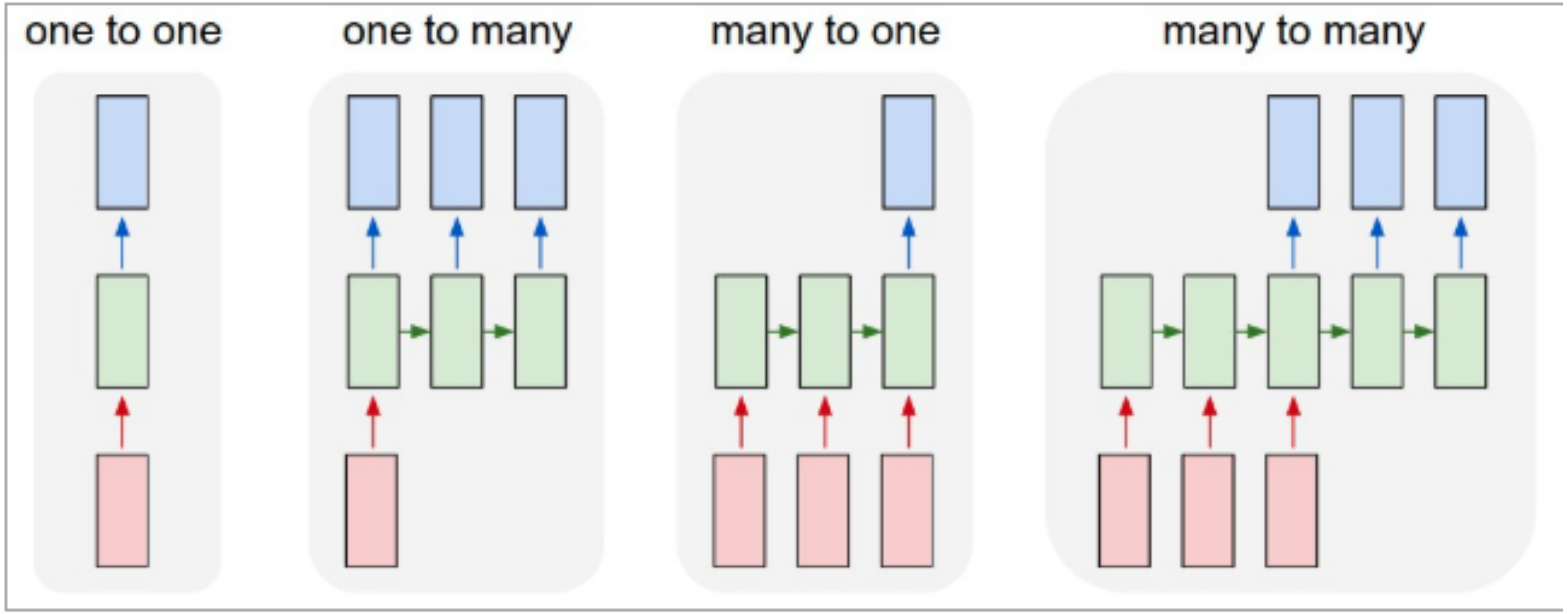
Sequence output

e.g., to know the sentiments of a sentence

Recurrent Neural Networks

CNNs,
fixed input,
fixed output

Sequence input



Sequence output

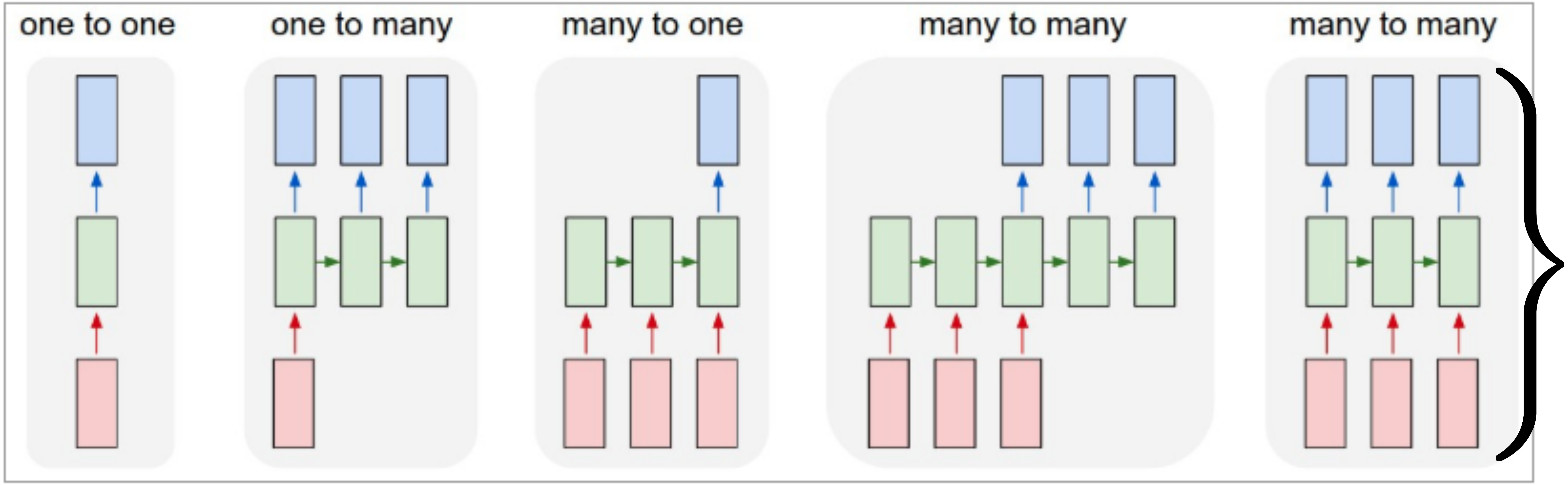
Sequence input,
Sequence output.
e.g. Machine translation

Recurrent Neural Networks

CNNs,
fixed input,
fixed output

Sequence input

Synced sequence
Input & output



e.g., video classification where we want to label each frame

Sequence output

Sequence input,
Sequence output.
e.g. Machine translation

Training

Input is a sequence of 7 frames

128x128 random image crop per sequence

Play the sequence forward/backward

Each frame advance the camera or random seed

Loss Functions

Spatial Loss to emphasize more the dark regions

$$L_s = \frac{1}{N}\sum_{i}^{N}|P_i - T_i|$$

Loss Functions

Spatial Loss to emphasize more the dark regions

$$L_s = \frac{1}{N}\sum_i^N |P_i - T_i|$$

Temporal loss

$$L_t = \frac{1}{N}\sum_i^N \left(\left| \frac{\partial P_i}{\partial t} - \frac{\partial T_i}{\partial t} \right| \right)$$

Loss Functions

Spatial Loss to emphasize more the dark regions

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Temporal loss

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High frequency error norm loss for stable edges

$$L_g = \frac{1}{N}\sum_{i}^{N}|\nabla P_i - \nabla T_i|$$

Loss Functions

Spatial Loss to emphasize more the dark regions

$$L_s = \frac{1}{N}\sum_{i}^{N}|P_i - T_i|$$

Temporal loss

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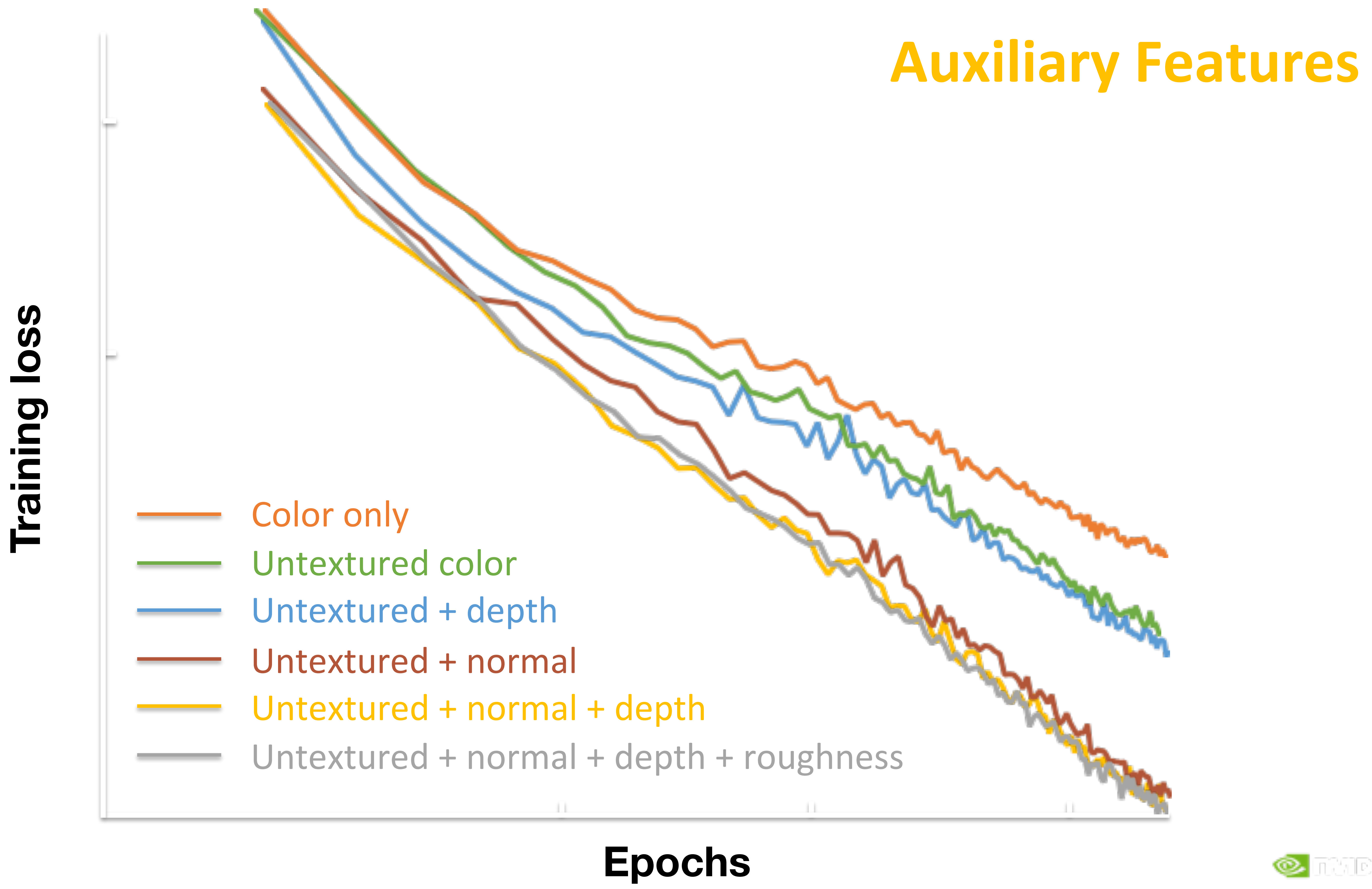
High frequency error norm loss for stable edges

$$L_g = \frac{1}{N}\sum_{i}^{N}|\nabla P_i - \nabla T_i|$$

Final Loss is a weighted averaged of above losses

$$L = w_s L_s + w_g L_g + w_t L_t$$

Training Loss depends on Auxiliary Features



Temporal Stability


Recurrent autoencoder
with temporal AA
Recurrent autoencoder
Autoencoder
with skips


Recurrent autoencoder
with temporal AA
Recurrent autoencoder
Autoencoder
with skips


1 sample/pixel input


1 sample/pixel input


Recurrent autoencoder
1 sample/pixel input


Recurrent autoencoder
1 sample/pixel input

Introduction to CNNs

Kernel Predicting Denoising

Sample-based MC Denoising

(next lecture)

Acknowledgments

Thanks to Chaitanya et al. for making their slides publicly available.