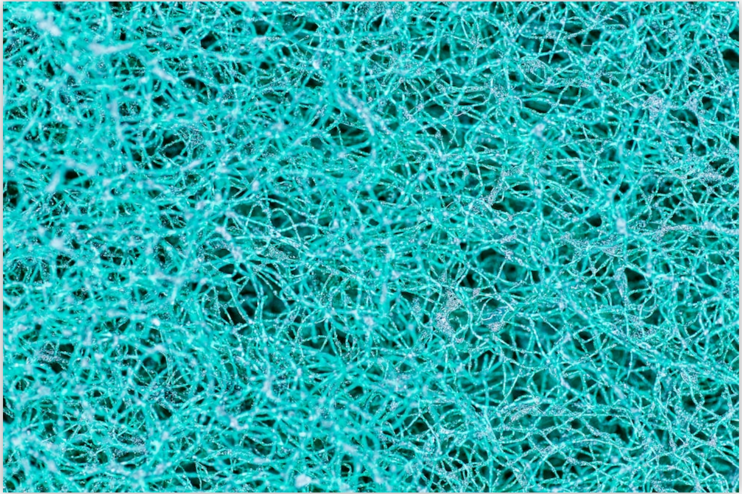
Introduction to Neural Networks

MLPs, CNNs, Backpropagation, Learned Image Processing



CSC2529

David Lindell

University of Toronto

cs.toronto.edu/~lindell/teaching/2529

*slides adapted from CS231n at Stanford

Announcements

- HW5 is out due Friday 11/10
- Problem session for HW5 tomorrow
- Start pairing up and thinking about projects (see course webpage for past projects).

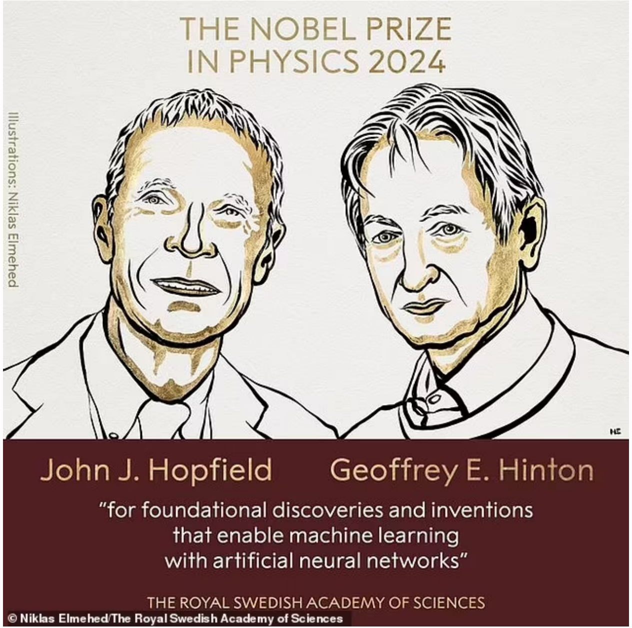
Announcements

Linfeng Ye

Hao Yang, Chu King Kung, Jangwon Suh

Roberto Rangel da Silva

Announcements



Announcements

Toronto Vision Seminar

Computer Science UNIVERSITY OF TORONTO

UNIVERSITY OF TORONTO FACULTY OF ARTS & SCIENCE

FIELDS

Kristina Monakhova

Assistant Professor Department of Computer Science, Cornell University

Wednesday, Oct 16th, 2024
3 PM – 4 PM (ET)

BA 5187

Reception to follow

Scan for Zoom link

“Trustworthy and adaptive extreme low light imaging”

Abstract:

Imaging in low light settings is challenging due to low photon counts. In photography, imaging under low light, high gain settings often results in highly structured, non-Gaussian noise that’s hard to characterize or denoise. In scanning microscopy, the push to image faster, deeper, with less damage, and for longer durations, can result in noisy measurements and less signal acquired. In this talk, we'll address three problems in denoising that are important for real applications: 1) What can you do when your noise is sensor-specific and non-Gaussian? 2) How can you trust the output of a denoiser enough for critical scientific and medical applications? and 3) If you can sample a noisy scene multiple times, which parts should you resample? For the first problem, I'll introduce a sensor-specific, data-driven, physics-inspired noise model for simulating camera noise at the lowest light and highest gain settings. I'll then use this noise model as a building block for demonstrating photorealistic videography by the light of only the stars (submillilux levels of illumination). Next, I'll introduce an uncertainty quantification technique based on conformal prediction to simultaneously denoise and predict the pixel-wise uncertainty in microscopy images. Then, I'll use uncertainty-in-the-loop to drive adaptive acquisition for scanning microscopy, reducing the total scan time and light dose to the sample, while minimizing uncertainty.

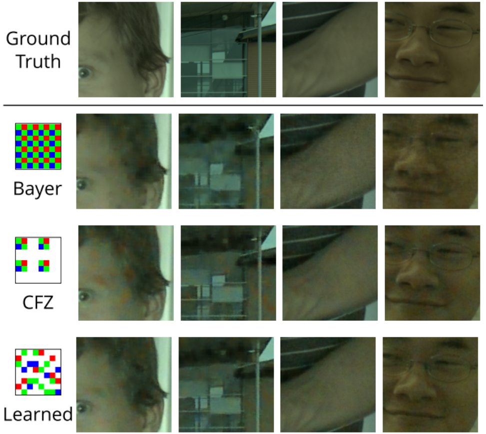
Biography:

Kristina Monakhova is an Assistant Professor in the Department of Computer Science at Cornell University, where she leads the Computational Imaging Lab at Cornell. She received her Ph.D. from UC Berkeley in Electrical Engineering and Computer Sciences and was a postdoctoral fellow at MIT, supported by the MIT Postdoctoral Fellowship for Engineering Excellence. Her research group focuses on co-designing optics and algorithms to create better, smaller, and more capable cameras and microscopes.

There is no registration for this event. However, seating is limited, so arriving early is recommended.

Neural Networks in Computational Imaging

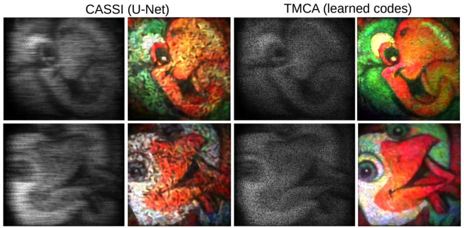
- Now: learned pipelines for computational imaging



Learning CFAs

(b) Raw data via traditional pipeline (c) Our result

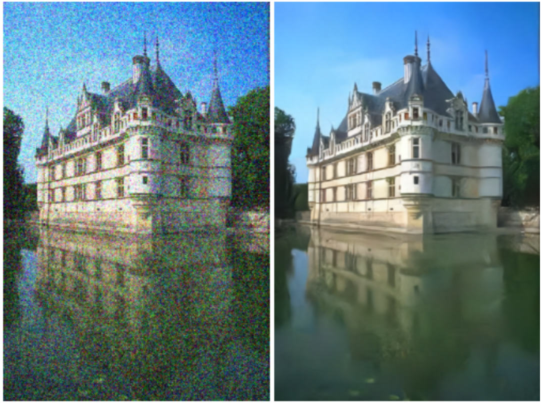
Learning ISPs



Learning coded apertures

Neural Networks in Computational Imaging

- Now: learned pipelines for computational imaging



Learned denoising

Learned deblurring

HDR Imaging

Today

- What is a neural network?
- Training/optimizing neural nets
- Why “neural”?
- Convolutional neural networks
- Applications & inverse problems

What is a neural network?

- Image classification example

Image Classification

- Image classification example

Images

MNIST Dataset

Image Classification

- Image classification example

Images

Class

“zero”
“one”

…

“nine”

Image Classification

- Image classification example

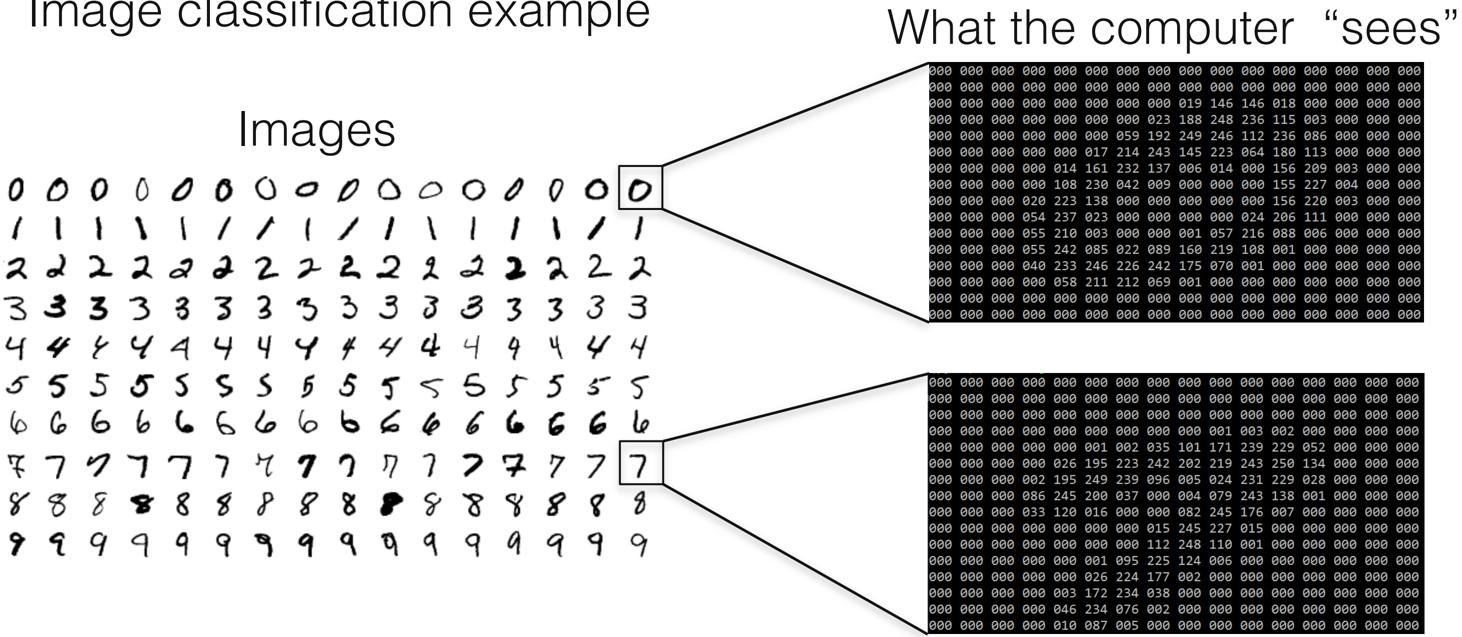
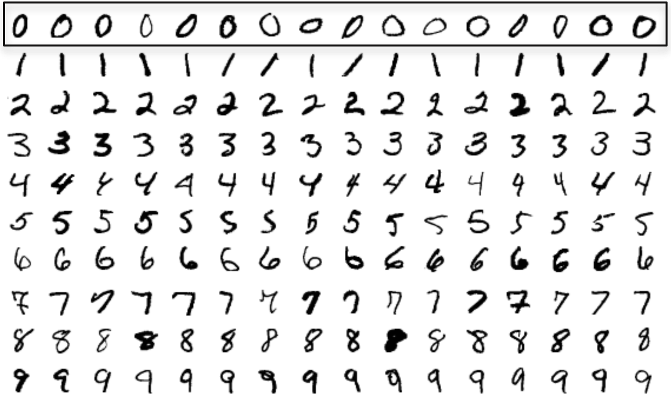


Image Classification

- Image classification example

Images



Challenges

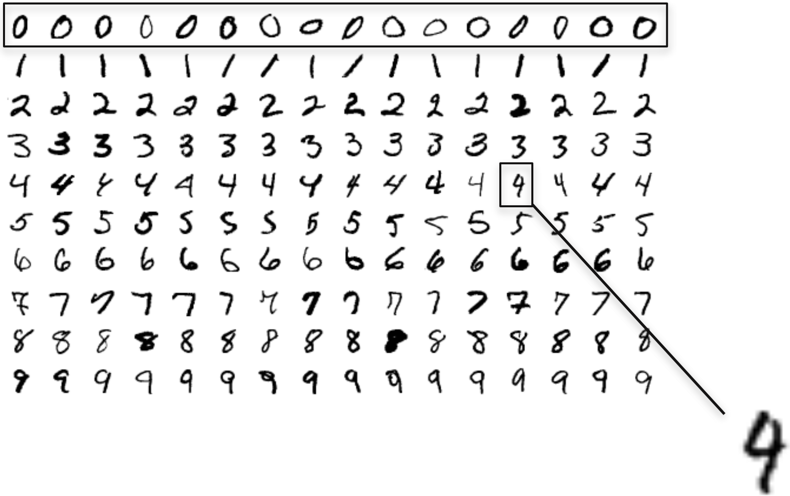
Intra-class variation

- stroke widths
- alignment
- writing styles

Image Classification

- Image classification example

Images



Challenges

Intra-class variation

- stroke widths
- alignment
- writing styles

Inter-class similarities

- “four” or “nine”?

Image Classification

- Image classification example

Images

Implementation?

```python
def classify_digit(image):
    # ???
    return image_class
```

Can't hardcode solution!

Image Classification

- Data-driven approach
    - Collect training images and labels
    - Train a classifier using machine learning
    - Evaluate the classifier on unseen images

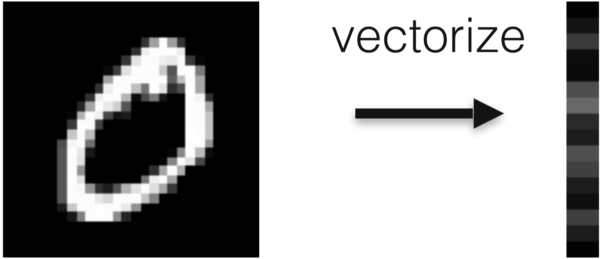
Implementation?

```python
def train(images, labels):
    # machine learning model
    return image_class

def evaluate(model, test_images):
    # machine learning model
    return test_labels

```

Image Classification

- Linear Model

$$f(x, W) = Wx$$



x

Image Classification

- Linear Model

$$f(x, W) = Wx$$

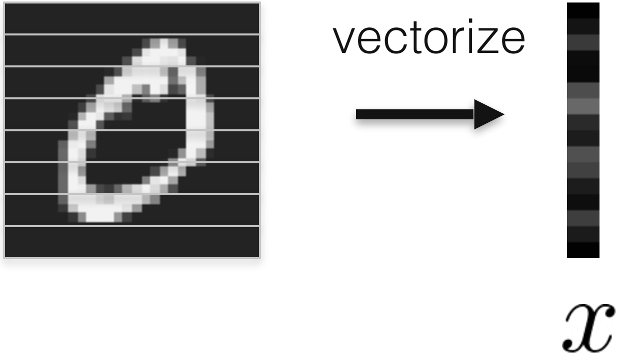


Image Classification

- Linear Model

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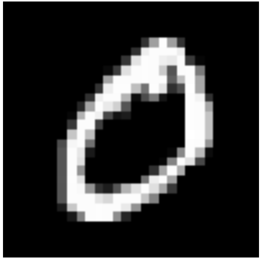
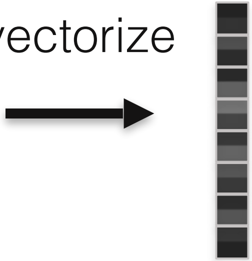


vectorize



x

Image Classification

- Linear Model

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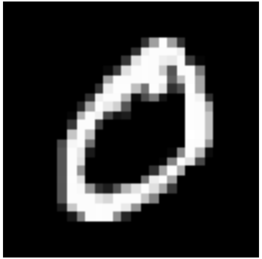

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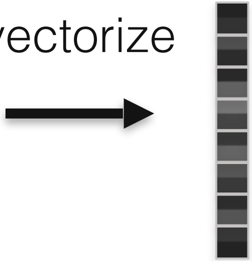


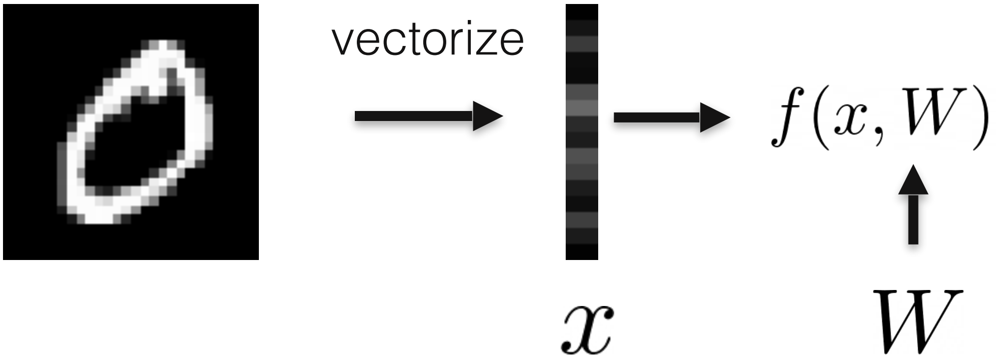
$$x$$

Length of this vector is the “dimensionality” of our problem!

Image Classification

- Linear Model

$$f(x, W) = Wx$$



$\boxed{\text{In general: } Wx + b}$

Image Classification

- Linear Model $f(x, W) = Wx$

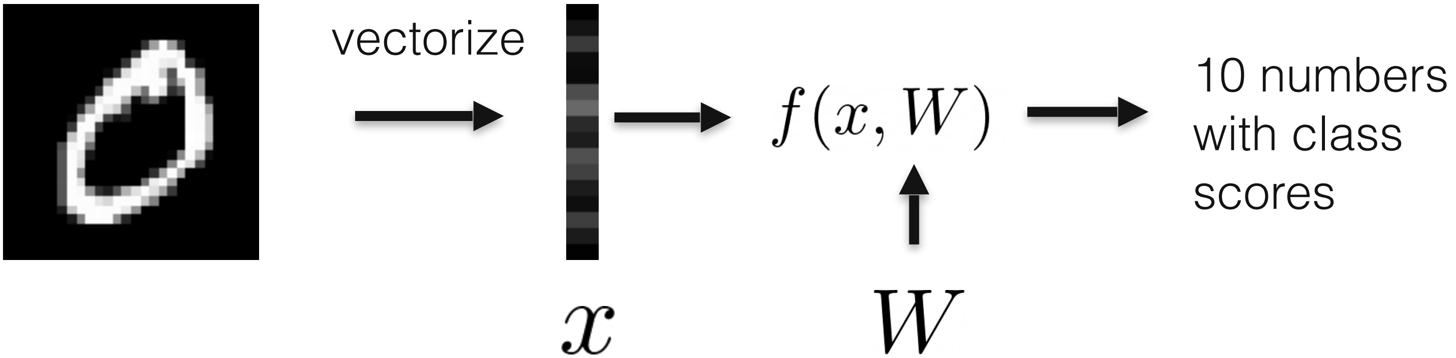
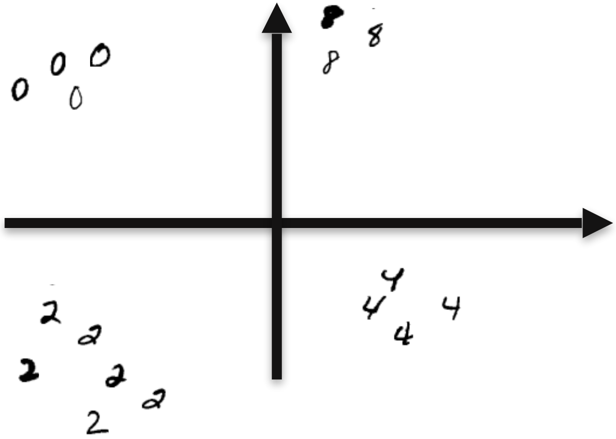


Image Classification

- Linear model: geometric intrepretation

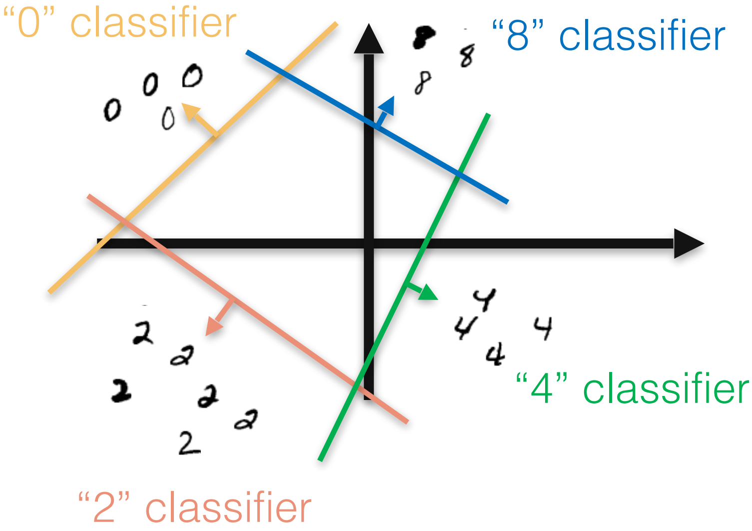


Each image is a point in an N-dimensional space

- N is the number of pixels

Image Classification

- Linear model: geometric interpretation



$$f(x, W) = Wx$$

Computes inner product between rows of W and x!

- Each row of W is a hyperplane
- Sign of inner product tells you which side of the hyperplane
- "separates" the digits

Image Classification

- Linear model (visual interpretation)

Learned filters (rows of W)

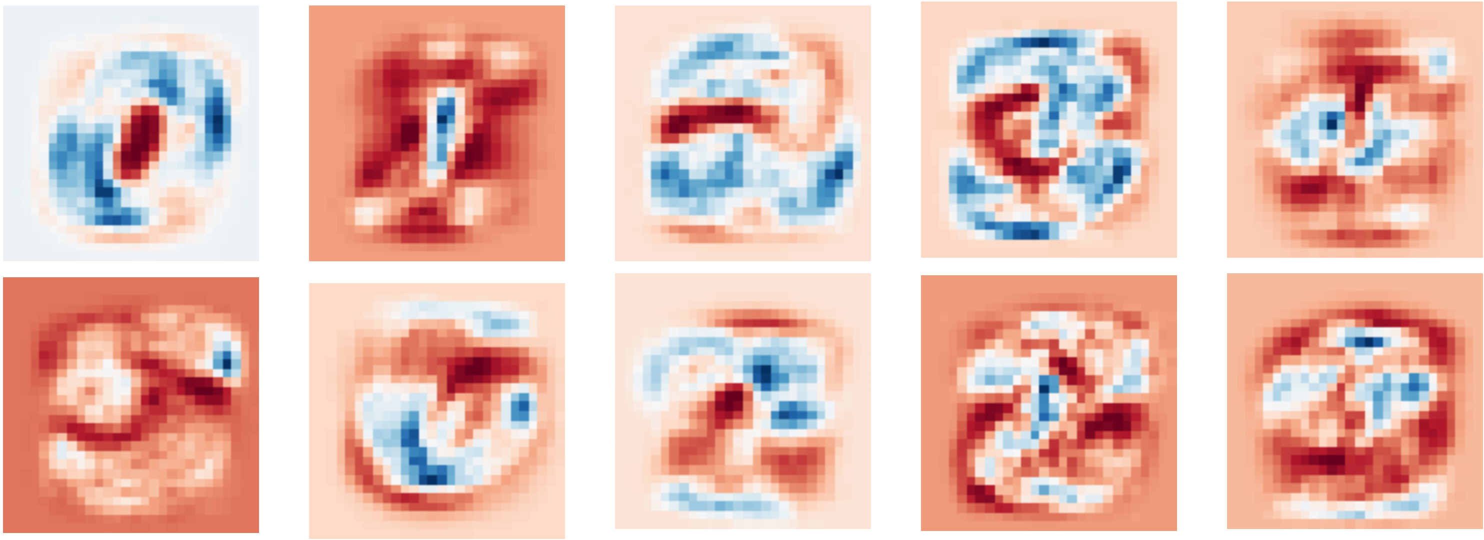
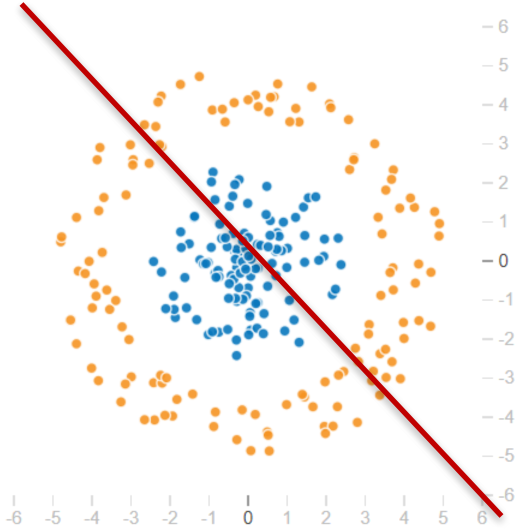


Image Classification

- Limits of linear classifiers

Linear classifiers learn linear decision planes

What if dataset is not linearly separable?



Multilayer Perceptrons (MLPs)

- Linear Model $f = Wx$
- 2-layer MLP $f = W_2 \max(0, W_1 x)$

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Non-linearity/activation function between linear layers

Multilayer Perceptrons (MLPs)

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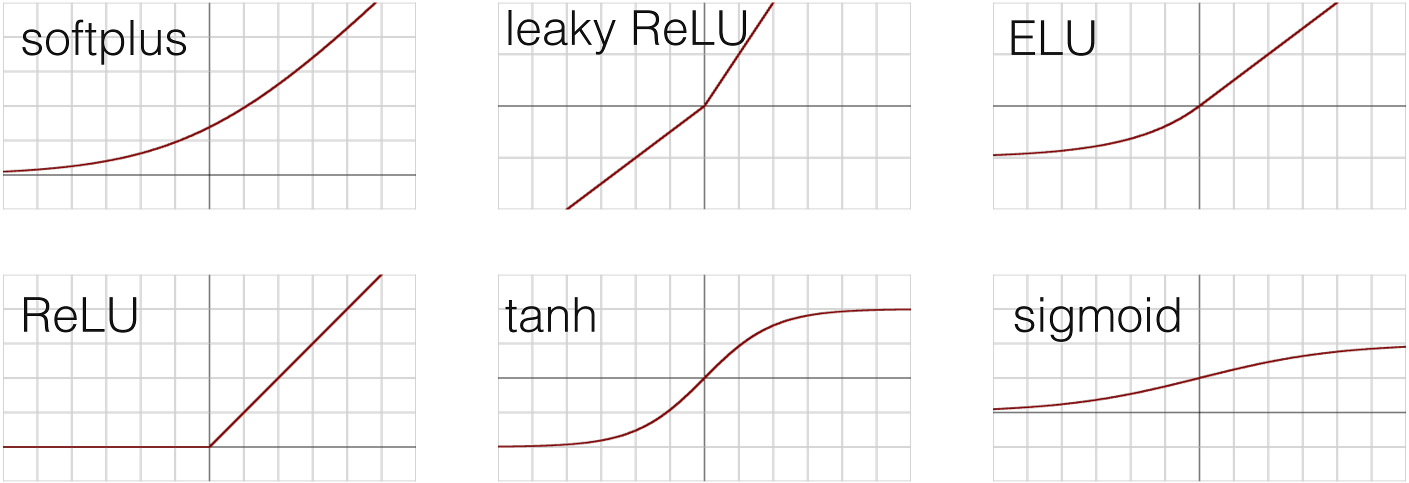
- 2-layer MLP $f = W_2 \max(0, W_1 x)$
- 3-layer MLP $f = W_3 \max(0, W_2 \max(0, W_1 x))$

Otherwise we have:

$$f = W_3 W_2 W_1 x$$

Activation Functions

…many to choose from

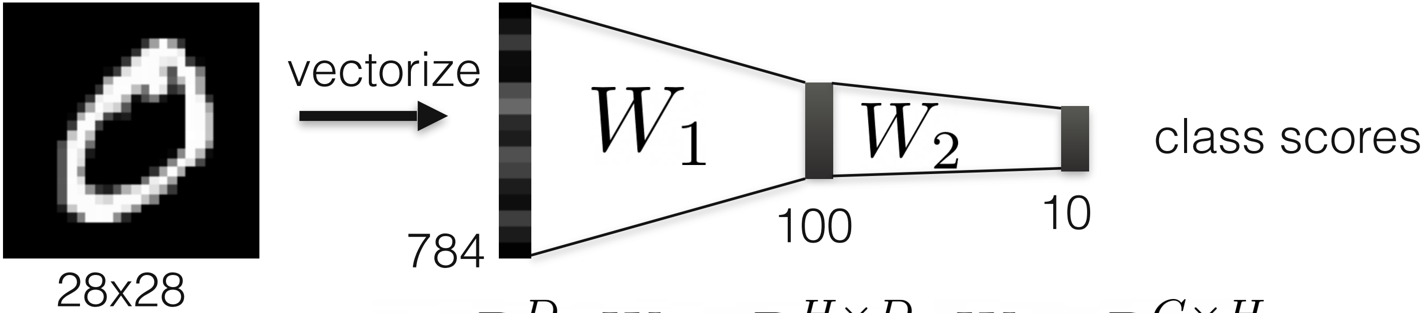


… ReLU is a good general-purpose choice: $\text{ReLU}(x) = \max(0, x)$

Multilayer Perceptrons (MLPs)

- Linear Model $f = Wx$
- 2-layer MLP $f = W_2 \max(0, W_1 x)$

Back to our classification example…



$$x \in \mathbb{R}^D,\ W_1 \in \mathbb{R}^{H \times D},\ W_2 \in \mathbb{R}^{C \times H}$$

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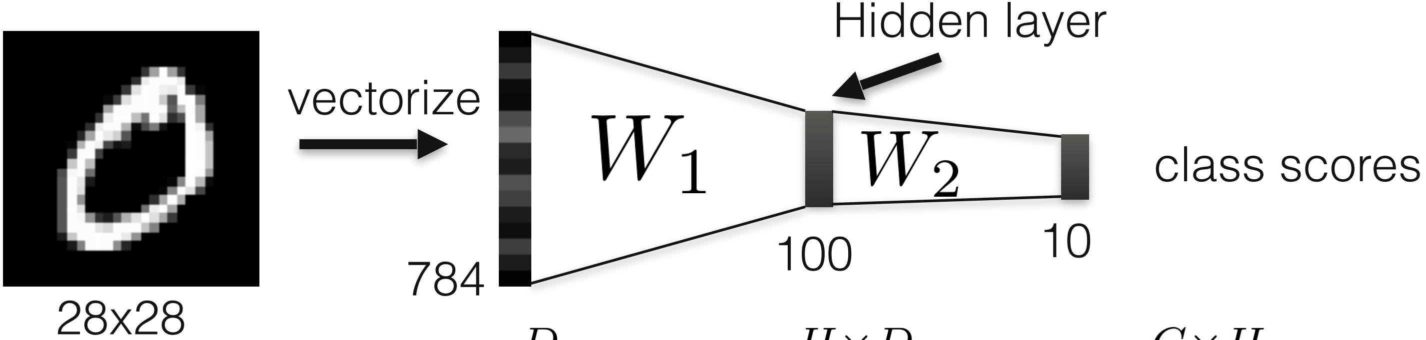

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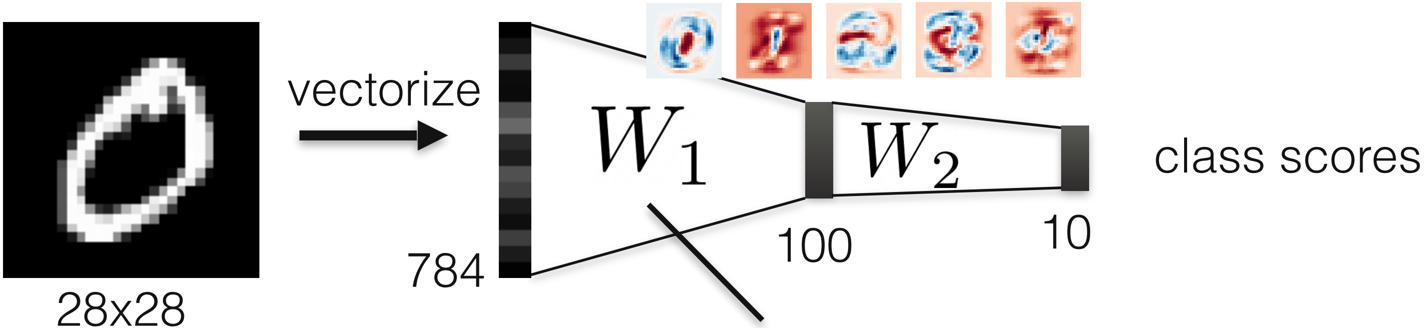


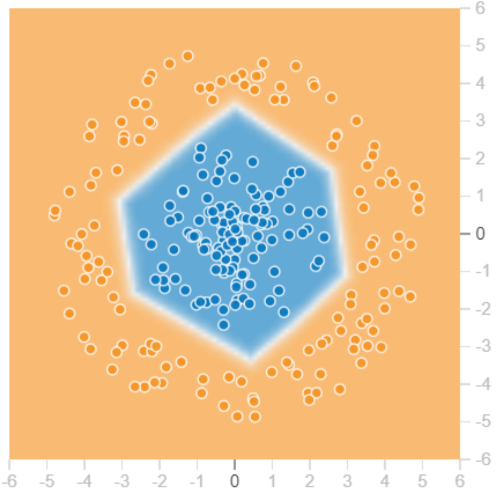
Now we have 100 shape templates, shared between classes

Multilayer Perceptrons (MLPs)

- Overcomes limits of linear classifiers

  - Can learn non-linear decision boundaries

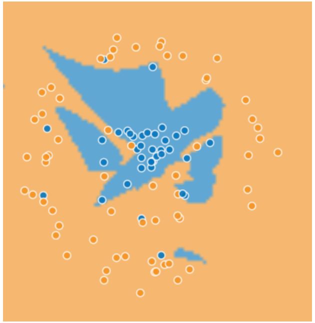
  - Complexity scales with the number of neurons/hidden layers



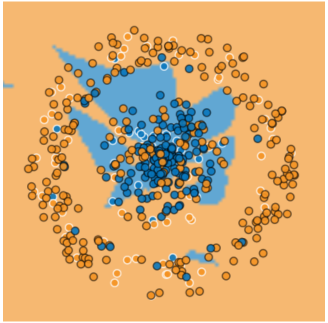
Multilayer Perceptrons (MLPs)

- More parameters is not always better!
  - Can lead to overfitting the training data
  - Performance on test data is worse

train



test

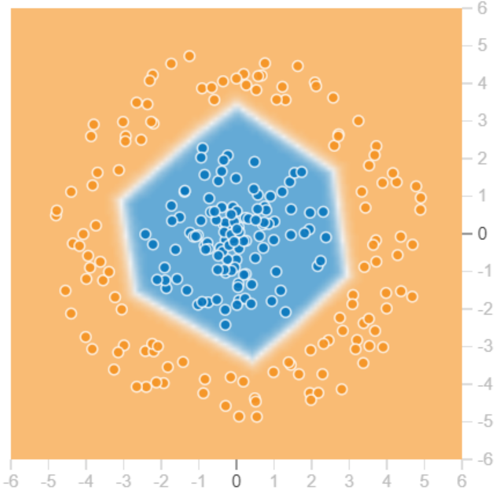


Multilayer Perceptrons (MLPs)

- More on classification…

  - https://cs231n.github.io/linear-classify/

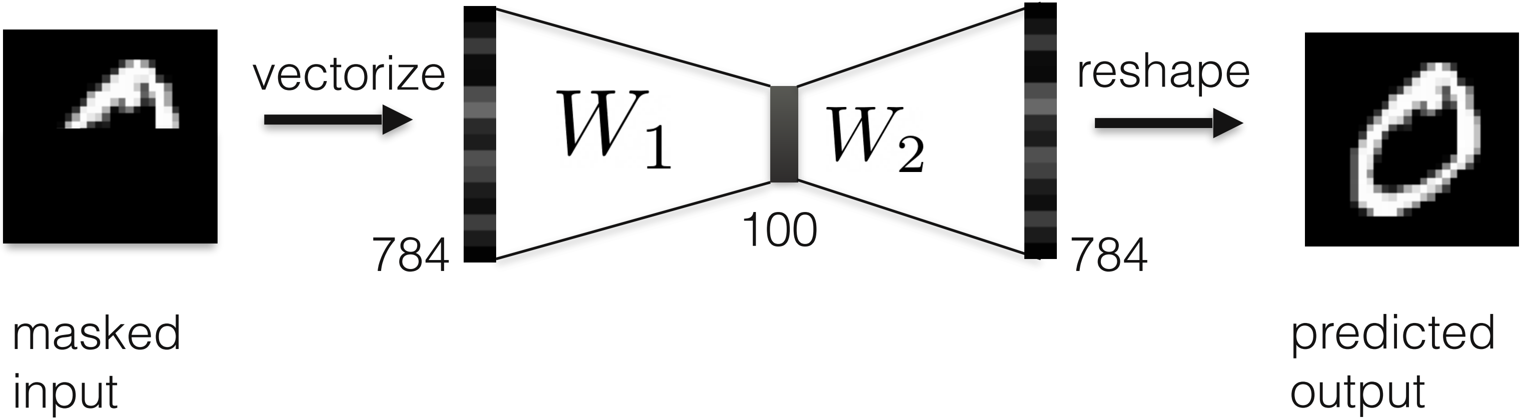
  - https://csc413-uoft.github.io/



Today

- What is a neural network?
- Training/optimizing neural nets
- Why “neural”?
- Convolutional neural networks
- Applications & inverse problems

Image Inpainting



Training the MLP

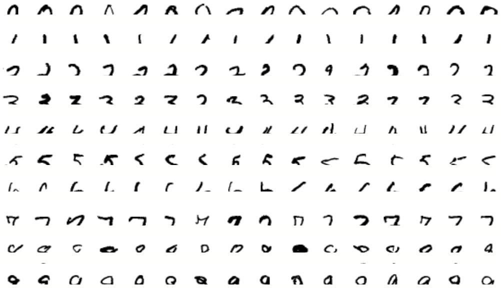
Image inpainting example

Training dataset:

- masked and complete image pairs

- train network to predict the complete image

masked images



ground truth

Training the MLP

Train the network to minimize the loss function

$$\mathcal{L}_\theta = \frac{1}{2}||y - \hat{y}||_2^2$$

network parameters

$\theta = \{W_1, W_2\}$

Training the MLP

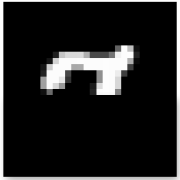
Train the network to minimize the loss function

$$\mathcal{L}_\theta = \frac{1}{2}||y - \hat{y}||_2^2$$

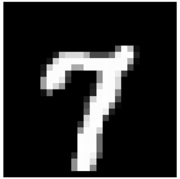
network parameters
$\theta = \{W_1, W_2\}$

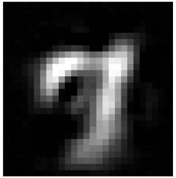
ground truth image

network prediction



input





Training the MLP

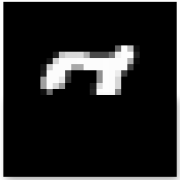
How do we figure out θ?

$$\mathcal{L}_\theta = \frac{1}{2}||y - \hat{y}||_2^2$$

network parameters
$\theta = \{W_1, W_2\}$

ground truth image

network prediction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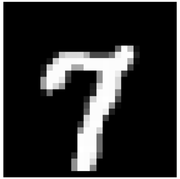
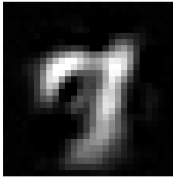
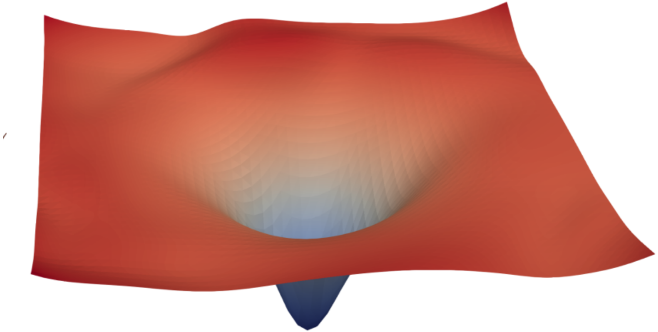




Training the MLP

Gradient-based optimization

$$\nabla_\theta \mathcal{L}_\theta$$



Loss Landscape

[Li et al. '18]

Training the MLP

$$\frac{\partial}{\partial W_1}\mathcal{L}_\theta = \frac{\partial}{\partial W_1}\frac{1}{2}\|y - \hat{y}\|_2^2$$

$$\frac{\partial}{\partial W_2}\mathcal{L}_\theta = \frac{\partial}{\partial W_2}\frac{1}{2}\|y - \hat{y}\|_2^2$$

Need to calculate the partial derivative with respect to each parameter

Training the MLP

Generally there are 3 options

1. Numerical differentiation
2. Symbolic differentiation
3. “Automatic” differentiation

Numerical Differentiation

$$\frac{\partial f(x)}{\partial x} \approx \lim_{h \to 0} \frac{f(x+h) - f(x)}{h}$$

Not very accurate, computationally expensive

Easy to implement! Can be used to check your analytical answers..

Symbolic Differentiation

$$
\begin{aligned}
\frac{\partial \mathcal{L}_\theta}{\partial W_1} &= \frac{\partial}{\partial W_1} \frac{1}{2} \|y - \hat{y}\|_2^2 \\
&= \frac{\partial}{\partial W_1} \frac{1}{2} \left(W_2 \sigma(W_1 x)\right)^T \left(W_2 \sigma(W_1 x)\right) \\
&= \frac{\partial}{\partial W_1} \frac{1}{2} \sigma(W_1 x)^T W_2^T W_2 \sigma(W_1 x) \\
&= \dots \quad \text{chain rule, product rule...}
\end{aligned}
$$

Accurate, but must be manually calculated for each term
Tedious!

Automatic Differentiation

Think about the problem as a “computational graph”

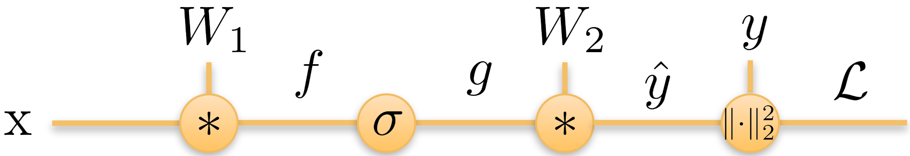
Divide and conquer using the chain rule

Enables “backpropagation” – an efficient way to take derivatives of all parameters in a computational graph

Automatic Differentiation

Think about the problem as a "computational graph"

Divide and conquer using the chain rule



Automatic Differentiation

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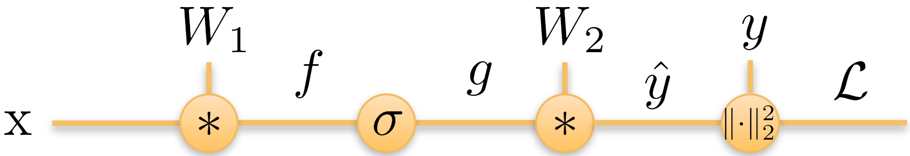
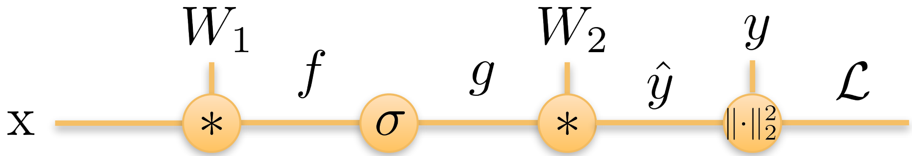


$$\frac{\partial \mathcal{L}}{\partial W_2} = \frac{\partial \hat{y}}{\partial W_2} \frac{\partial \mathcal{L}}{\partial \hat{y}}$$

Automatic Differentiation

Think about the problem as a "computational graph"

Divide and conquer using the chain rule

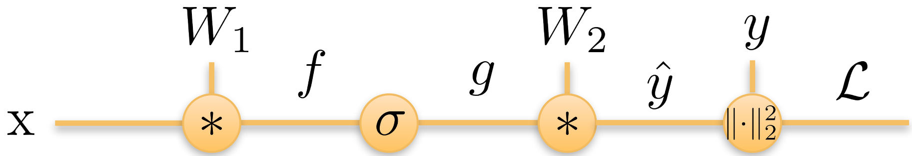


$$\frac{\partial \mathcal{L}}{\partial W_1} = \frac{\partial f}{\partial W_1}\frac{\partial g}{\partial f}\frac{\partial \hat{y}}{\partial g}\frac{\partial \mathcal{L}}{\partial \hat{y}}$$

Automatic Differentiation

Think about the problem as a "computational graph"

Divide and conquer using the chain rule

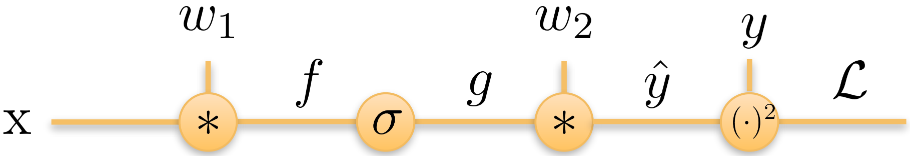


$$\frac{\partial \mathcal{L}}{\partial W_1} = \frac{\partial f}{\partial W_1}\frac{\partial g}{\partial f}\frac{\partial \hat{y}}{\partial g}\frac{\partial \mathcal{L}}{\partial \hat{y}}$$

We can calculate analytical expressions for each of these terms and then plug in our values

Autodiff Example

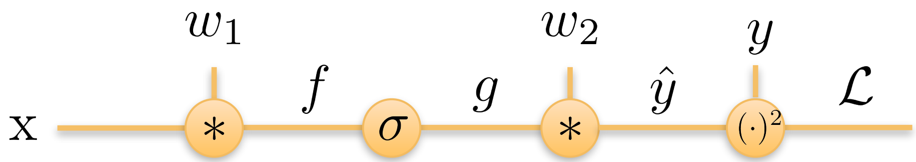
(assume scalar values for now)



$$\frac{\partial \mathcal{L}}{\partial w_1} = \frac{\partial f}{\partial w_1} \frac{\partial g}{\partial f} \frac{\partial \hat{y}}{\partial g} \boxed{\frac{\partial \mathcal{L}}{\partial \hat{y}}}$$

Autodiff Example

(assume scalar values for now)

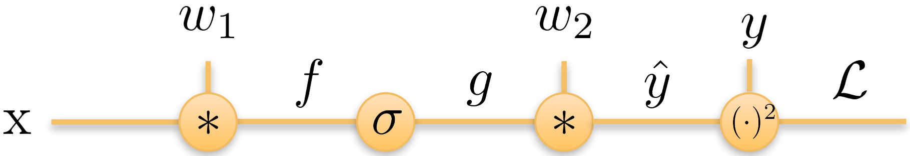


$$\frac{\partial \mathcal{L}}{\partial w_1} = \frac{\partial f}{\partial w_1}\frac{\partial g}{\partial f}\frac{\partial \hat{y}}{\partial g}\boxed{\frac{\partial \mathcal{L}}{\partial \hat{y}}}$$

$$\frac{\partial \mathcal{L}}{\partial \hat{y}} = \frac{\partial}{\partial \hat{y}}\frac{1}{2}(\hat{y}-y)^2 = \hat{y}-y$$

Autodiff Example

(assume scalar values for now)

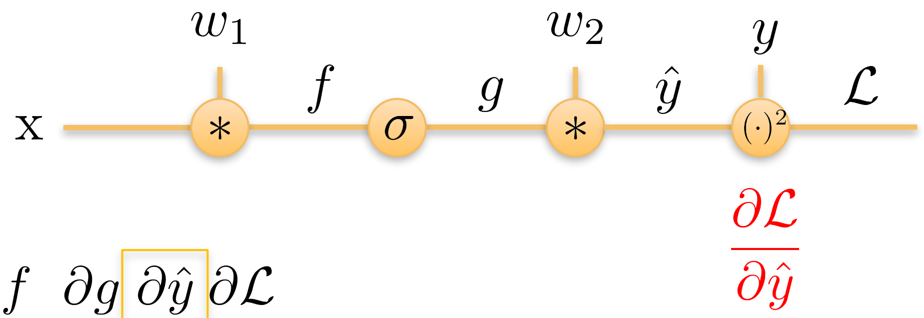


$$\frac{\partial \mathcal{L}}{\partial \hat{y}}$$

$$\frac{\partial \mathcal{L}}{\partial w_1} = \frac{\partial f}{\partial w_1} \frac{\partial g}{\partial f} \boxed{\frac{\partial \hat{y}}{\partial g}} \frac{\partial \mathcal{L}}{\partial \hat{y}}$$

Autodiff Example

(assume scalar values for now)

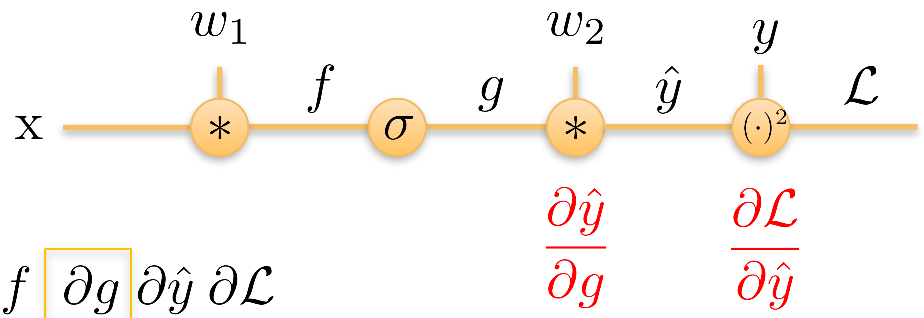


$$\frac{\partial \mathcal{L}}{\partial w_1} = \frac{\partial f}{\partial w_1} \frac{\partial g}{\partial f} \boxed{\frac{\partial \hat{y}}{\partial g}} \frac{\partial \mathcal{L}}{\partial \hat{y}}$$

$$\frac{\partial \hat{y}}{\partial g} = \frac{\partial}{\partial g} w_2 \cdot g = w_2$$

Autodiff Example

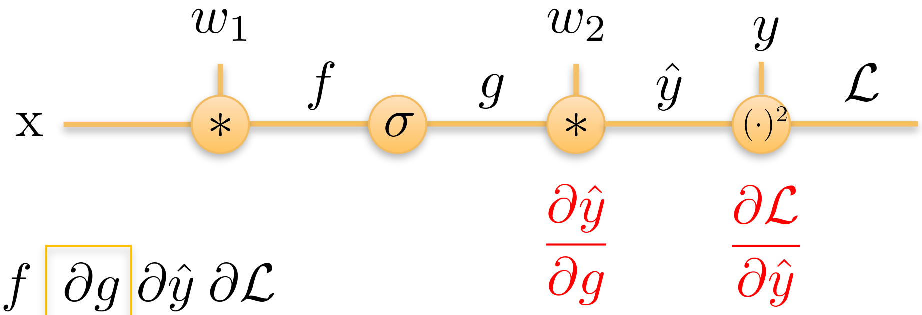
(assume scalar values for now)



$$\frac{\partial \mathcal{L}}{\partial w_1} = \frac{\partial f}{\partial w_1} \boxed{\frac{\partial g}{\partial f}} \frac{\partial \hat{y}}{\partial g} \frac{\partial \mathcal{L}}{\partial \hat{y}}$$

Autodiff Example

(assume scalar values for now)

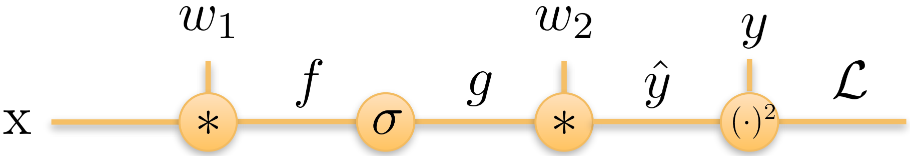


$$\frac{\partial \mathcal{L}}{\partial w_1} = \frac{\partial f}{\partial w_1} \boxed{\frac{\partial g}{\partial f}} \frac{\partial \hat{y}}{\partial g} \frac{\partial \mathcal{L}}{\partial \hat{y}}$$

$$\frac{\partial g}{\partial f} = \frac{\partial}{\partial f}\sigma(f) = \frac{\partial}{\partial f}\max(0, f) = \begin{cases} 0, & f < 0 \\ 1 & \text{else} \end{cases}$$

Autodiff Example

(assume scalar values for now)

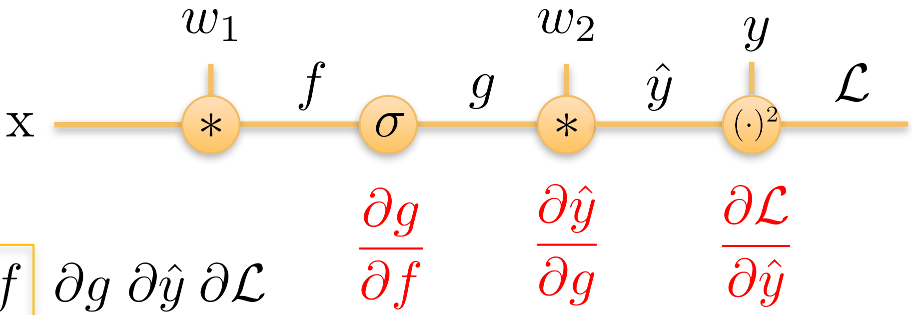


$$\frac{\partial g}{\partial f} \qquad \frac{\partial \hat{y}}{\partial g} \qquad \frac{\partial \mathcal{L}}{\partial \hat{y}}$$

$$\frac{\partial \mathcal{L}}{\partial w_1} = \boxed{\frac{\partial f}{\partial w_1}} \frac{\partial g}{\partial f} \frac{\partial \hat{y}}{\partial g} \frac{\partial \mathcal{L}}{\partial \hat{y}}$$

Autodiff Example

(assume scalar values for now)

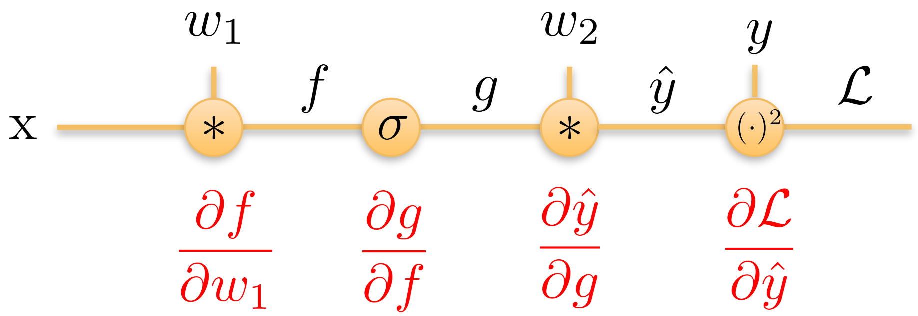


$$\frac{\partial \mathcal{L}}{\partial w_1} = \boxed{\frac{\partial f}{\partial w_1}} \frac{\partial g}{\partial f} \frac{\partial \hat{y}}{\partial g} \frac{\partial \mathcal{L}}{\partial \hat{y}}$$

$$\frac{\partial f}{\partial w_1} = \frac{\partial}{\partial w_1} w_1 \cdot x = x$$

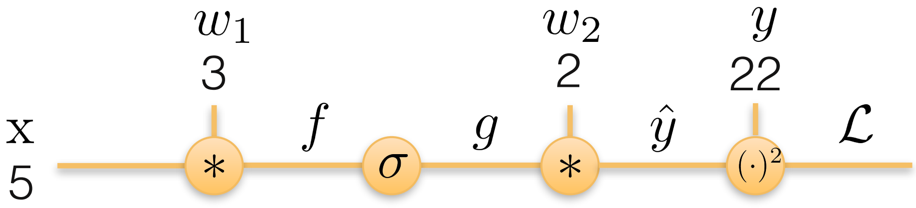
Autodiff Example

(assume scalar values for now)



Autodiff Example

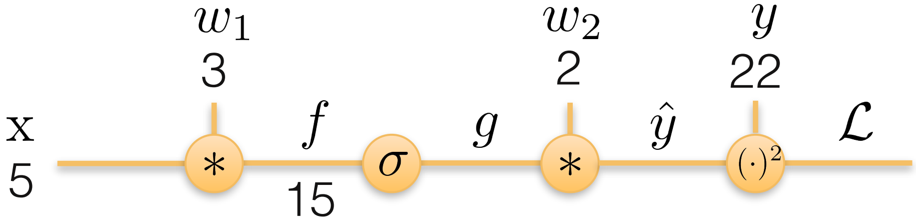
Let's plug in the values now…



$$\frac{\partial f}{\partial w_1} \qquad \frac{\partial g}{\partial f} \qquad \frac{\partial \hat{y}}{\partial g} \qquad \frac{\partial \mathcal{L}}{\partial \hat{y}}$$

Autodiff Example

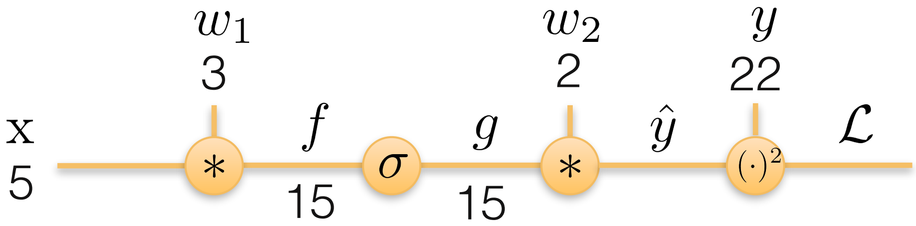
Let's plug in the values now…



$$\frac{\partial f}{\partial w_1} \quad \frac{\partial g}{\partial f} \quad \frac{\partial \hat{y}}{\partial g} \quad \frac{\partial \mathcal{L}}{\partial \hat{y}}$$

Autodiff Example

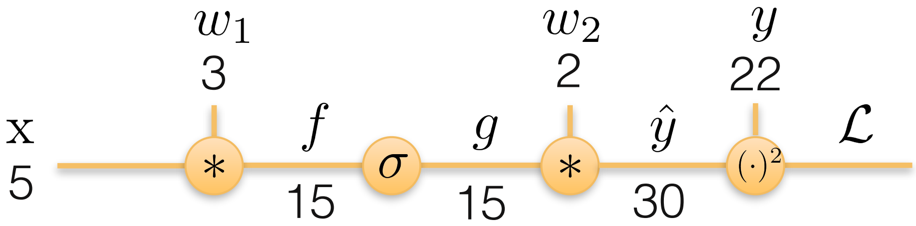
Let's plug in the values now…



$$\frac{\partial f}{\partial w_1} \quad \frac{\partial g}{\partial f} \quad \frac{\partial \hat{y}}{\partial g} \quad \frac{\partial \mathcal{L}}{\partial \hat{y}}$$

Autodiff Example

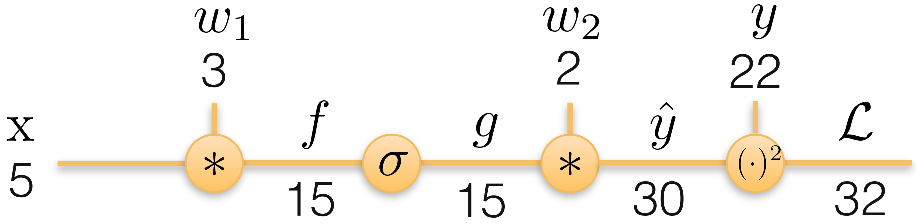
Let's plug in the values now…



$$\frac{\partial f}{\partial w_1} \qquad \frac{\partial g}{\partial f} \qquad \frac{\partial \hat{y}}{\partial g} \qquad \frac{\partial \mathcal{L}}{\partial \hat{y}}$$

Autodiff Example

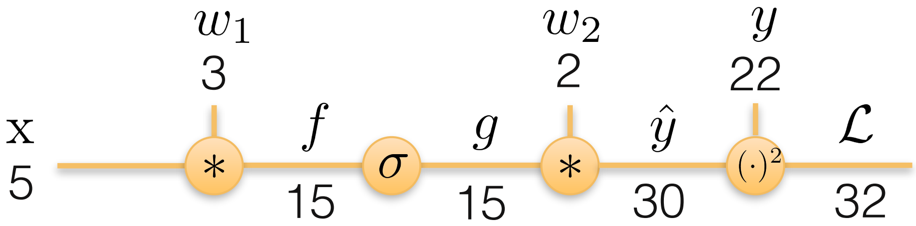
Let's plug in the values now…



$$\frac{\partial f}{\partial w_1} \qquad \frac{\partial g}{\partial f} \qquad \frac{\partial \hat{y}}{\partial g} \qquad \frac{\partial \mathcal{L}}{\partial \hat{y}}$$

Autodiff Example

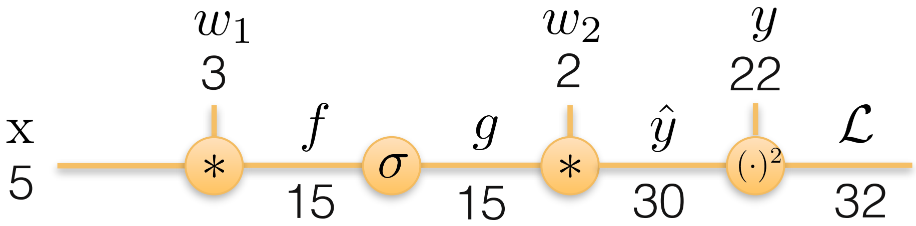
Let’s plug in the values now…



$$\frac{\partial f}{\partial w_1} \qquad \frac{\partial g}{\partial f} \qquad \frac{\partial \hat{y}}{\partial g} \qquad \frac{\partial \mathcal{L}}{\partial \hat{y}} = \hat{y} - y$$

Autodiff Example

Let's plug in the values now…

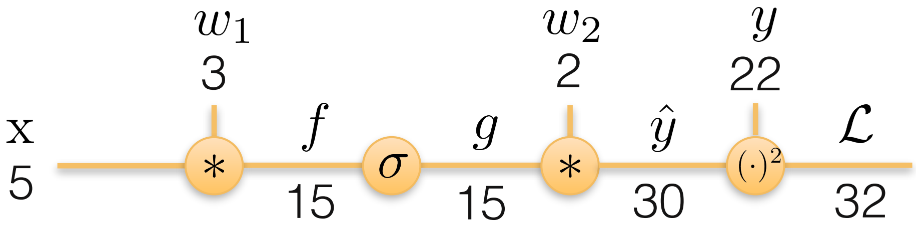


$$\frac{\partial f}{\partial w_1} \qquad \frac{\partial g}{\partial f} \qquad \frac{\partial \hat{y}}{\partial g} \qquad \frac{\partial \mathcal{L}}{\partial \hat{y}} = \hat{y} - y$$

8

Autodiff Example

Let's plug in the values now…

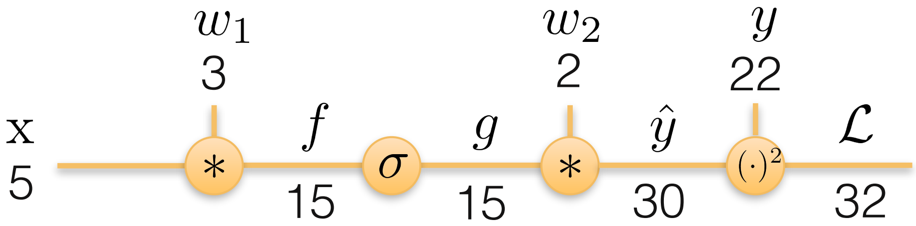


$$\frac{\partial f}{\partial w_1} \qquad \frac{\partial g}{\partial f} \qquad \frac{\partial \hat{y}}{\partial g} \qquad \frac{\partial \mathcal{L}}{\partial \hat{y}} = \hat{y} - y$$

2   8

Autodiff Example

Let's plug in the values now…

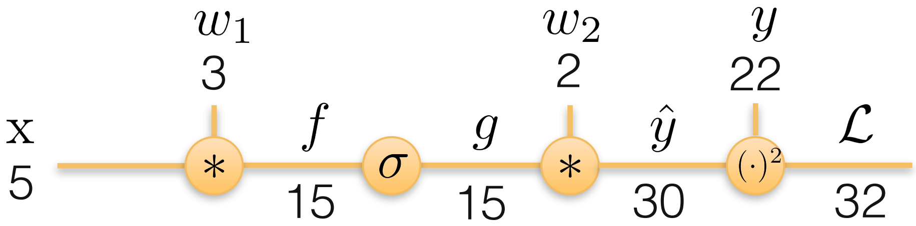


$$\frac{\partial f}{\partial w_1} \qquad \frac{\partial g}{\partial f} \qquad \frac{\partial \hat{y}}{\partial g} \qquad \frac{\partial \mathcal{L}}{\partial \hat{y}} = \hat{y} - y$$

1 2 8

Autodiff Example

Let's plug in the values now…

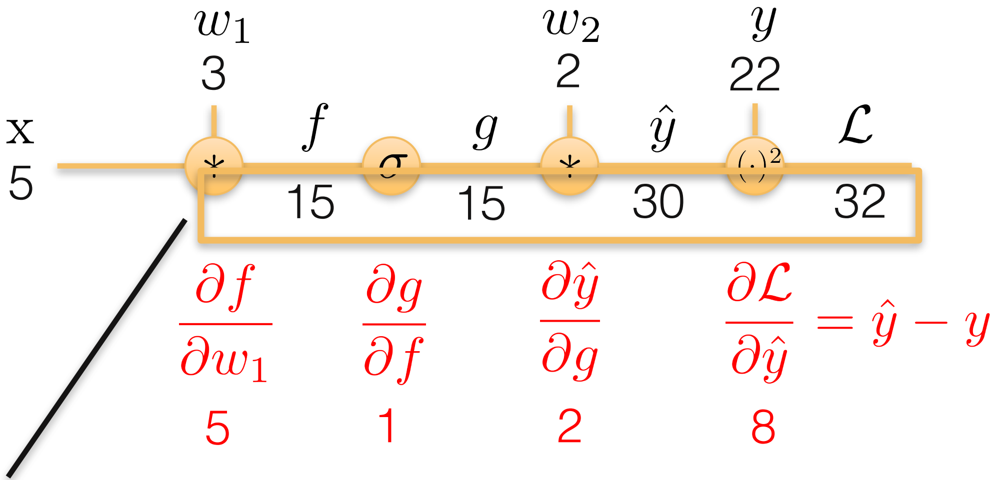


$$\frac{\partial f}{\partial w_1} \qquad \frac{\partial g}{\partial f} \qquad \frac{\partial \hat{y}}{\partial g} \qquad \frac{\partial \mathcal{L}}{\partial \hat{y}} = \hat{y} - y$$

5 1 2 8

Autodiff Example

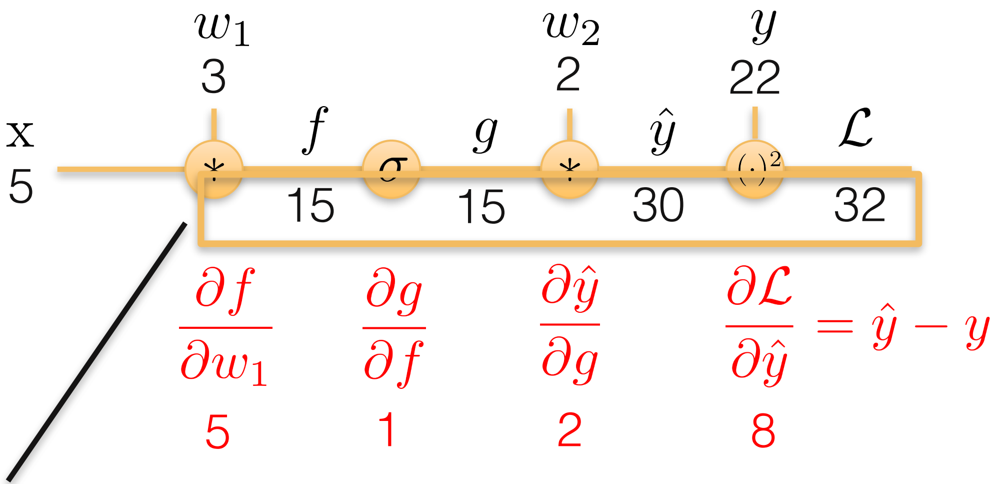
What is backpropagation?



Save these intermediate values during forward computation

Autodiff Example

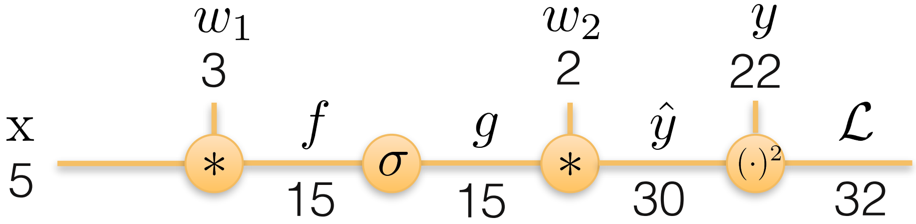
What is backpropagation?



Then we perform a “backward pass”

Autodiff Example

What is backpropagation?



$$\frac{\partial f}{\partial w_1}$$
5

$$\frac{\partial g}{\partial f}$$
1

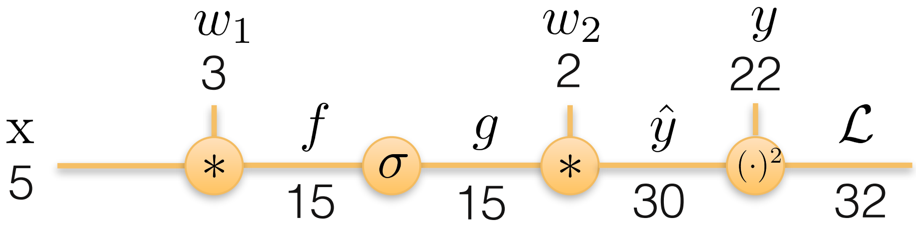
$$\frac{\partial \hat{y}}{\partial g}$$
2

$$\frac{\partial \mathcal{L}}{\partial g}$$

$$\frac{\partial \mathcal{L}}{\partial \hat{y}} = \hat{y} - y$$
8

Autodiff Example

What is backpropagation?



$$\frac{\partial f}{\partial w_1}$$
5

$$\frac{\partial g}{\partial f}$$
1

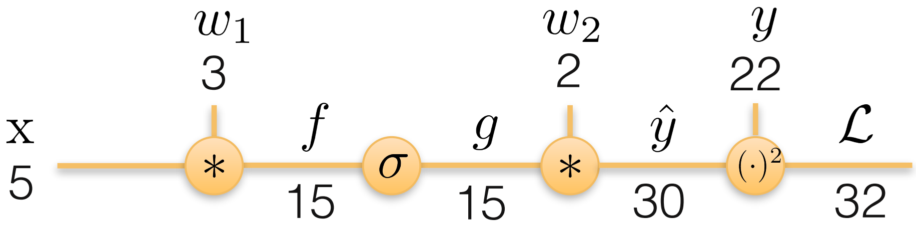
$$\frac{\partial \hat{y}}{\partial g}$$
2

$$\frac{\partial \mathcal{L}}{\partial g}$$
16

$$\frac{\partial \mathcal{L}}{\partial \hat{y}} = \hat{y} - y$$
8

Autodiff Example

What is backpropagation?



$$\frac{\partial f}{\partial w_1}$$
5

$$\frac{\partial g}{\partial f}$$
1

$$\frac{\partial \mathcal{L}}{\partial f}$$

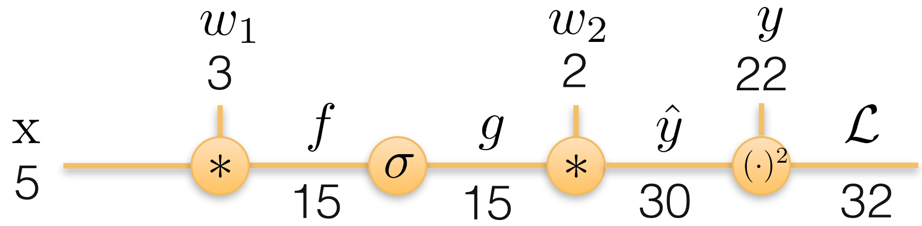
$$\frac{\partial \hat{y}}{\partial g}$$
2

$$\frac{\partial \mathcal{L}}{\partial g}$$
16

$$\frac{\partial \mathcal{L}}{\partial \hat{y}} = \hat{y} - y$$
8

Autodiff Example

What is backpropagation?



$$\frac{\partial f}{\partial w_1}$$
5

$$\frac{\partial g}{\partial f}$$
1

$$\frac{\partial \hat{y}}{\partial g}$$
2

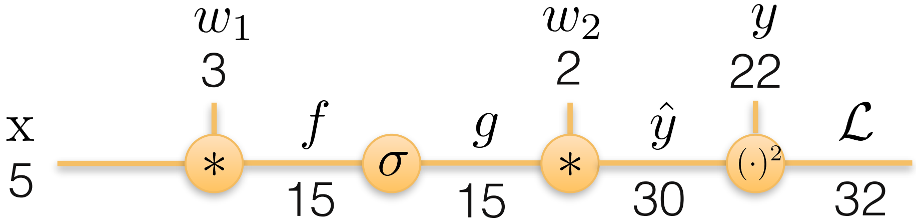
$$\frac{\partial \mathcal{L}}{\partial \hat{y}} = \hat{y} - y$$
8

$$\frac{\partial \mathcal{L}}{\partial f}$$
16

$$\frac{\partial \mathcal{L}}{\partial g}$$
16

Autodiff Example

What is backpropagation?



$$\frac{\partial f}{\partial w_1} \quad \frac{\partial g}{\partial f} \quad \frac{\partial \hat{y}}{\partial g} \quad \frac{\partial \mathcal{L}}{\partial \hat{y}} = \hat{y} - y$$

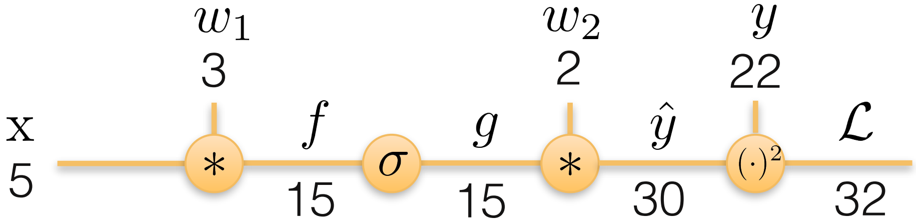
5 1 2 8

$$\frac{\partial \mathcal{L}}{\partial w_1} \quad \frac{\partial \mathcal{L}}{\partial f} \quad \frac{\partial \mathcal{L}}{\partial g}$$

16 16

Autodiff Example

What is backpropagation?



$$\frac{\partial f}{\partial w_1} \qquad \frac{\partial g}{\partial f} \qquad \frac{\partial \hat{y}}{\partial g} \qquad \frac{\partial \mathcal{L}}{\partial \hat{y}} = \hat{y} - y$$

5   1   2   8

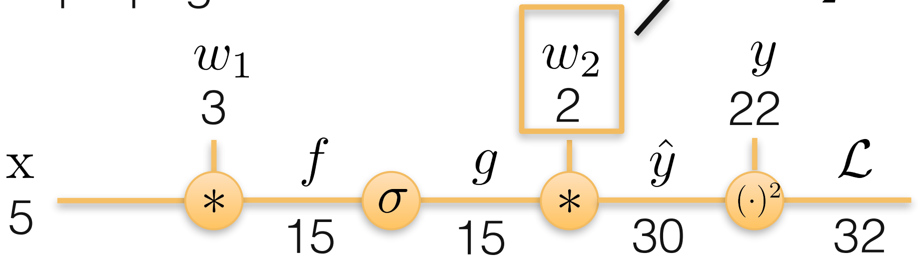
$$\frac{\partial \mathcal{L}}{\partial w_1} \qquad \frac{\partial \mathcal{L}}{\partial f} \qquad \frac{\partial \mathcal{L}}{\partial g}$$

80   16   16

Autodiff Example

What is backpropagation?

What about $\frac{\partial \mathcal{L}}{\partial w_2}$?



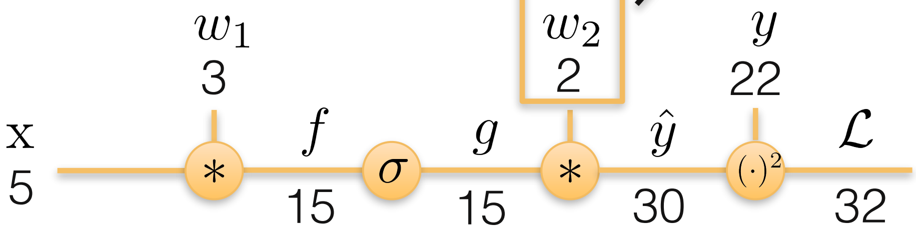
$$\frac{\partial f}{\partial w_1} = 5 \qquad \frac{\partial g}{\partial f} = 1 \qquad \frac{\partial \hat{y}}{\partial g} = 2 \qquad \frac{\partial \mathcal{L}}{\partial \hat{y}} = \hat{y} - y = 8$$

$$\frac{\partial \mathcal{L}}{\partial w_1} = 80 \qquad \frac{\partial \mathcal{L}}{\partial f} = 16 \qquad \frac{\partial \mathcal{L}}{\partial g} = 16$$

Autodiff Example

What is backpropagation?

What about $\frac{\partial \mathcal{L}}{\partial w_2}$?



$$\frac{\partial f}{\partial w_1} \quad 5 \qquad \frac{\partial g}{\partial f} \quad 1 \qquad \frac{\partial \hat{y}}{\partial g} \quad 2$$

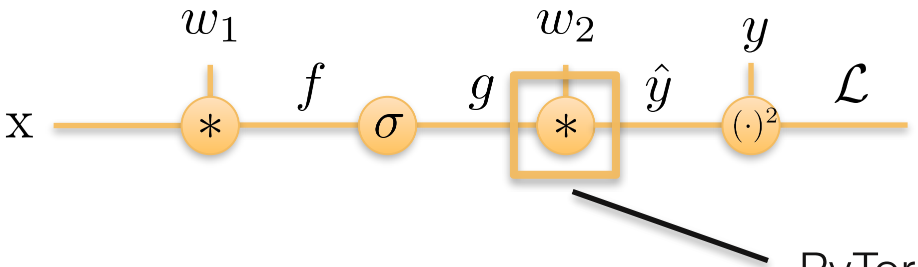
$$\frac{\partial \mathcal{L}}{\partial w_1} \quad 80 \qquad \frac{\partial \mathcal{L}}{\partial f} \quad 16 \qquad \frac{\partial \mathcal{L}}{\partial g} \quad 16$$

$$\boxed{\frac{\partial \mathcal{L}}{\partial \hat{y}}} = \hat{y} - y$$

We can re-use computation!

$$\frac{\partial \mathcal{L}}{\partial w_2} = \frac{\partial \hat{y}}{\partial w_2} \boxed{\frac{\partial \mathcal{L}}{\partial \hat{y}}}$$

Autodiff Example



PyTorch Code:

```
class Multiply(torch.autograd.Function):
  @staticmethod
  def forward(ctx, x, y):
    ctx.save_for_backward(x, y)
    z = x * y
    return z
  @staticmethod
  def backward(ctx, grad_z):
    x, y = ctx.saved_tensors
    grad_x = y * grad_z    # dz/dx * dL/dz
    grad_y = x * grad_z    # dz/dy * dL/dz
    return grad_x, grad_y
```

Need to stash some values for use in backward

Upstream gradient

Multiply upstream and local gradients

Image Inpainting Training Loop

1. Sample batch of images from dataset

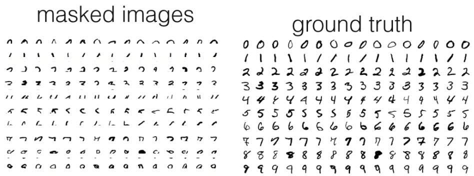
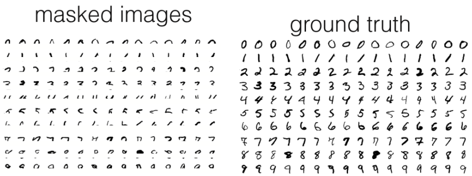


Image Inpainting Training Loop

1. Sample batch of images from dataset



2. Run forward pass to calculate network output for each image

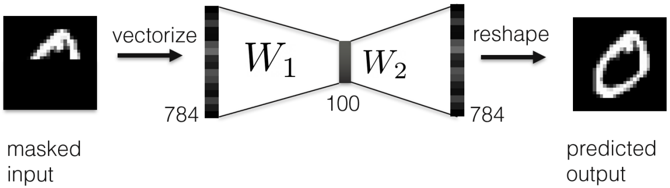
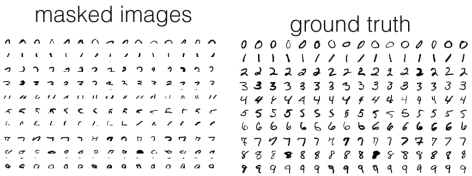
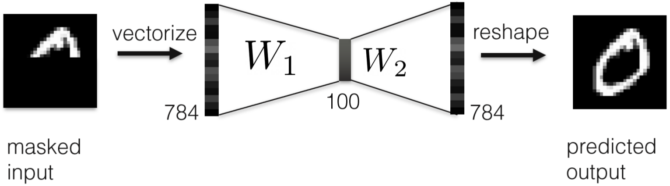


Image Inpainting Training Loop

1. Sample batch of images from dataset



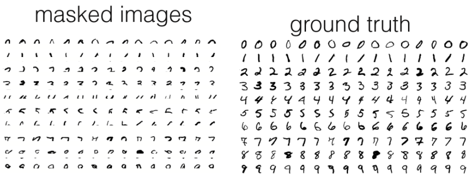
2. Run forward pass to calculate network output for each image



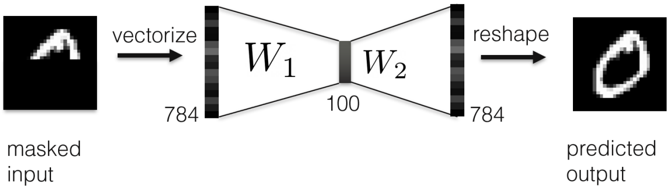
3. Run backward pass to calculate gradients with backpropagation

Image Inpainting Training Loop

1. Sample batch of images from dataset



2. Run forward pass to calculate network output for each image



3. Run backward pass to calculate gradients with backpropagation

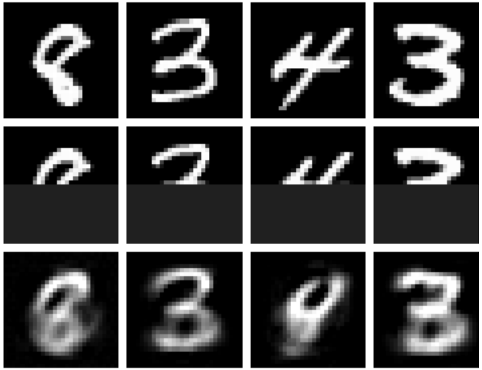
4. Update parameters with stochastic gradient descent

4. Update parameters with stochastic gradient descent

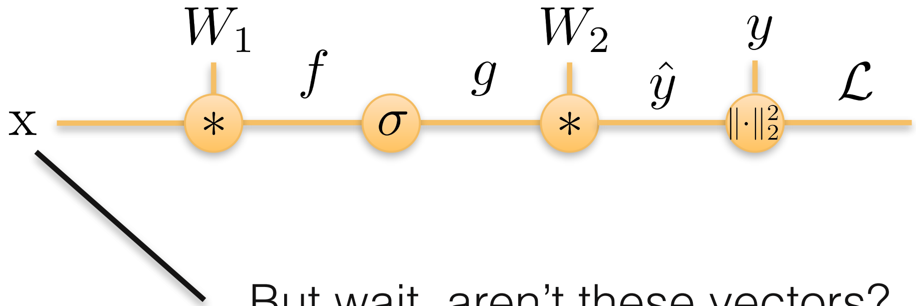
$$\mathcal{L}_\theta = \|y - \hat{y}\|_2^2$$

$$W_2^{(k+1)} = W_2^{(k)} - \alpha \frac{\partial \mathcal{L}}{\partial W_2}$$

$$W_1^{(k+1)} = W_1^{(k)} - \alpha \frac{\partial \mathcal{L}}{\partial W_1}$$

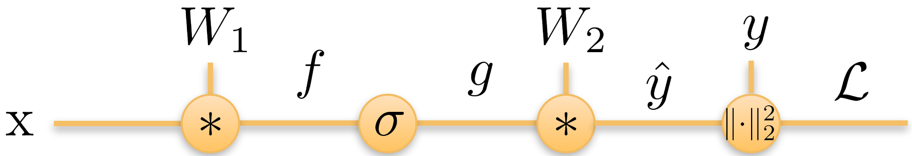


Vector Differentiation



But wait, aren't these vectors?

Vector Differentiation



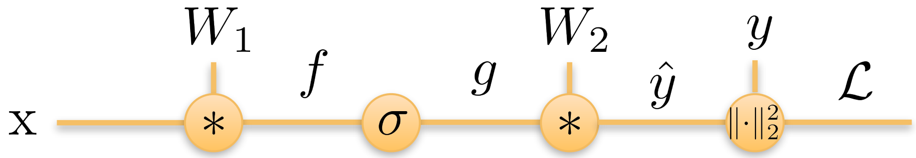
Recap: vector differentiation

Scalar by Scalar

$$x, y \in \mathbb{R}$$

$$\frac{\partial y}{\partial x} \in \ ?$$

Vector Differentiation



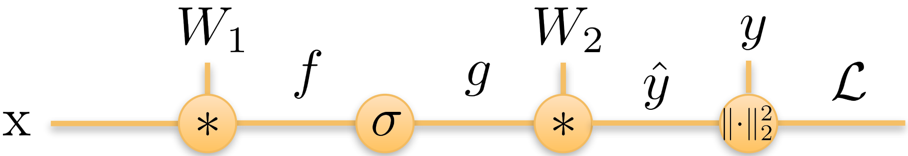
Recap: vector differentiation

Scalar by Scalar

$$x, y \in \mathbb{R}$$

$$\frac{\partial y}{\partial x} \in \mathbb{R}$$

Vector Differentiation



Recap: vector differentiation

Scalar by Scalar

$$x, y \in \mathbb{R}$$

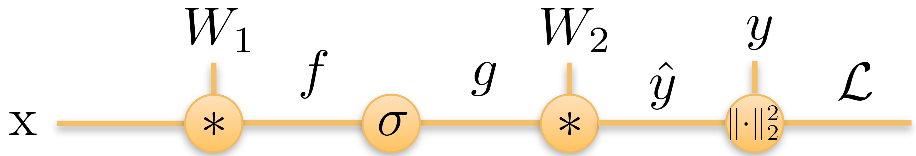
$$\frac{\partial y}{\partial x} \in \mathbb{R}$$

Scalar by Vector

$$x \in \mathbb{R}^N, y \in \mathbb{R}$$

$$\frac{\partial y}{\partial x} \in \quad ?$$

Vector Differentiation



Recap: vector differentiation

Scalar by Scalar

$$x, y \in \mathbb{R}$$

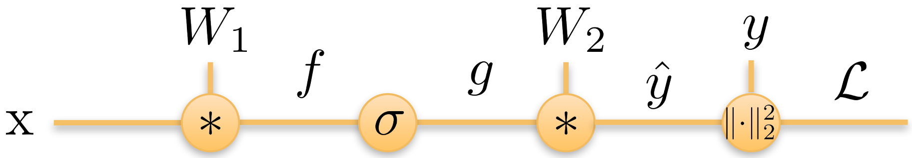
$$\frac{\partial y}{\partial x} \in \mathbb{R}$$

Scalar by Vector

$$x \in \mathbb{R}^N, y \in \mathbb{R}$$

$$\frac{\partial y}{\partial x} \in \mathbb{R}^N$$

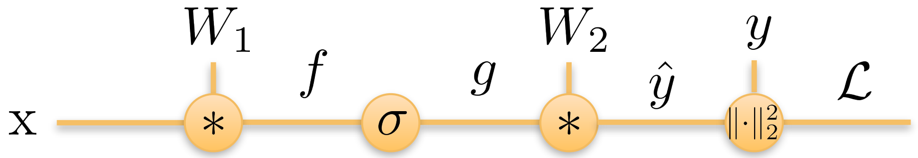
Vector Differentiation



Recap: vector differentiation

Scalar by Scalar	Scalar by Vector	Vector by Vector
$x, y \in \mathbb{R}$	$x \in \mathbb{R}^N, y \in \mathbb{R}$	$x \in \mathbb{R}^N, y \in \mathbb{R}^M$
$\dfrac{\partial y}{\partial x} \in \mathbb{R}$	$\dfrac{\partial y}{\partial x} \in \mathbb{R}^N$	$\dfrac{\partial y}{\partial x} \in$?

Vector Differentiation



Recap: vector differentiation

Scalar by Scalar	Scalar by Vector	Vector by Vector
$x, y \in \mathbb{R}$	$x \in \mathbb{R}^N, y \in \mathbb{R}$	$x \in \mathbb{R}^N, y \in \mathbb{R}^M$
$\frac{\partial y}{\partial x} \in \mathbb{R}$	$\frac{\partial y}{\partial x} \in \mathbb{R}^N$	$\frac{\partial y}{\partial x} \in \mathbb{R}^{N \times M}$

Vector Differentiation

$$w \in \mathbb{R}^P \rightarrow x \in \mathbb{R}^N \rightarrow y \in \mathbb{R}^M$$

$$\frac{\partial x}{\partial w} \in \mathbb{R}^{P \times N} \qquad \frac{\partial y}{\partial x} \in \mathbb{R}^{N \times M}$$

Vector Differentiation

$$\underset{\in \mathbb{R}^P}{w} \rightarrow \underset{\in \mathbb{R}^N}{x} \rightarrow \underset{\in \mathbb{R}^M}{y}$$

$$\frac{\partial x}{\partial w} \in \mathbb{R}^{P \times N} \qquad \frac{\partial y}{\partial x} \in \mathbb{R}^{N \times M}$$

$$\frac{\partial y}{\partial w} = \frac{\partial x}{\partial w}\frac{\partial y}{\partial x} \in \mathbb{R}^{P \times M}$$

Vector Differentiation

$$w \rightarrow x \rightarrow y$$

$$w \in \mathbb{R}^P \qquad x \in \mathbb{R}^N \qquad y \in \mathbb{R}^M$$

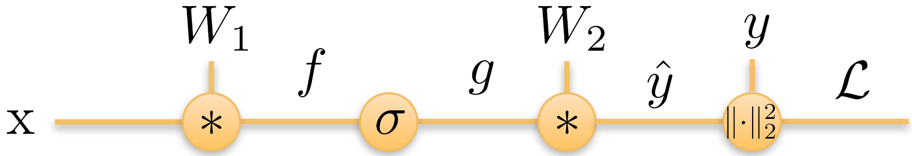
$$\frac{\partial x}{\partial w} \in \mathbb{R}^{P \times N} \qquad \frac{\partial y}{\partial x} \in \mathbb{R}^{N \times M}$$

$$\frac{\partial y}{\partial w} = \frac{\partial x}{\partial w}\frac{\partial y}{\partial x} \in \mathbb{R}^{P \times M}$$

sometimes the Jacobian is defined as the transpose of this, depending on whether you left or right multiply

(I like to left multiply because it aligns with the direction of the computational graph)

Recap: vector differentiation



Example 1: matrix multiply

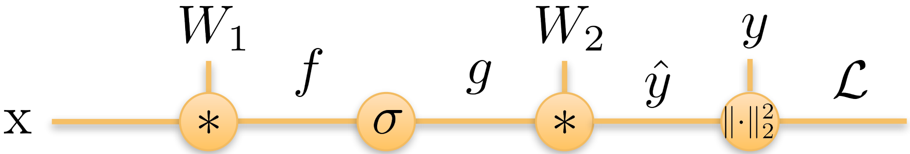
$$\frac{\partial \hat{y}}{\partial g} = \frac{\partial}{\partial g} W_2 g$$

$$W_2 \in \mathbb{R}^{M \times N}$$

$$g \in \mathbb{R}^N$$

$$\frac{\partial \hat{y}}{\partial g} \in \mathbb{R}^{N \times M}$$

Recap: vector differentiation



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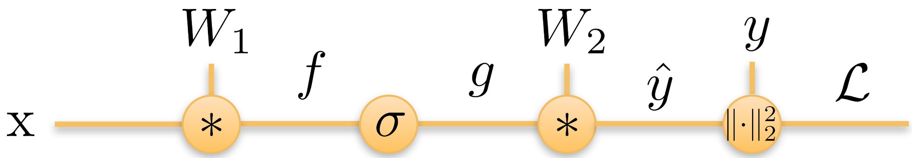
$$\frac{\partial}{\partial g} W_2 g$$

$$= \frac{\partial}{\partial g} \begin{bmatrix} w_{11} g_1 + \cdots + w_{1n} g_n \\ \vdots \quad \ddots \quad \vdots \\ w_{m1} g_1 + \cdots + w_{mn} g_n \end{bmatrix}$$

Recap: vector differentiation



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$$\frac{\partial \hat{y}}{\partial g} \in \mathbb{R}^{N \times M}$$

$$\boxed{\frac{\partial \hat{y}}{\partial g} = \begin{bmatrix} \frac{\partial \hat{y}_1}{\partial g_1} & \cdots & \frac{\partial \hat{y}_m}{\partial g_1} \\ \vdots & \ddots & \vdots \\ \frac{\partial \hat{y}_1}{\partial g_n} & \cdots & \frac{\partial \hat{y}_m}{\partial g_n} \end{bmatrix}}$$

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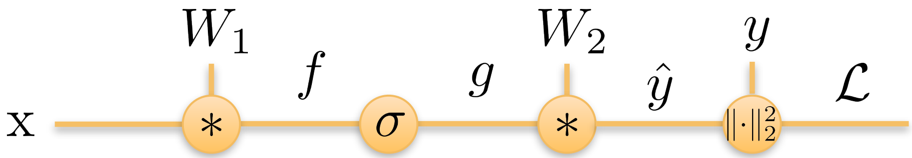
Recap: vector differentiation



$$\frac{\partial \hat{y}}{\partial g} = \begin{bmatrix} \frac{\partial \hat{y}_1}{\partial g_1} & \cdots & \frac{\partial \hat{y}_m}{\partial g_1} \\ \vdots & \ddots & \vdots \\ \frac{\partial \hat{y}_1}{\partial g_n} & \cdots & \frac{\partial \hat{y}_m}{\partial g_n} \end{bmatrix}$$

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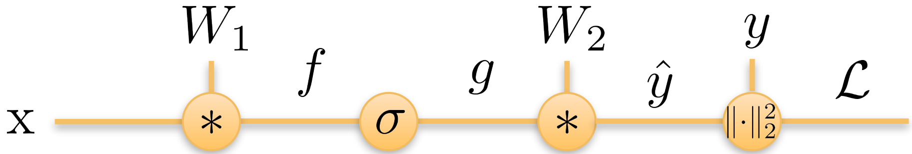
Recap: vector differentiation



$$\frac{\partial \hat{y}}{\partial g} = \begin{bmatrix} \frac{\partial \hat{y}_1}{\partial g_1} & \cdots & \frac{\partial \hat{y}_m}{\partial g_1} \\ \vdots & \ddots & \vdots \\ \frac{\partial \hat{y}_1}{\partial g_n} & \cdots & \frac{\partial \hat{y}_m}{\partial g_n} \end{bmatrix}$$

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$$= \boxed{W_2^T}$$

Recap: vector differentiation

Example 2: elementwise functions

$$h = f \odot g$$

$$f \in \mathbb{R}^N$$

$$g \in \mathbb{R}^N$$

$$\frac{\partial h}{\partial f} \in \mathbb{R}^{N \times N}$$

Recap: vector differentiation

Example 2: elementwise functions

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$$f \in \mathbb{R}^N$$

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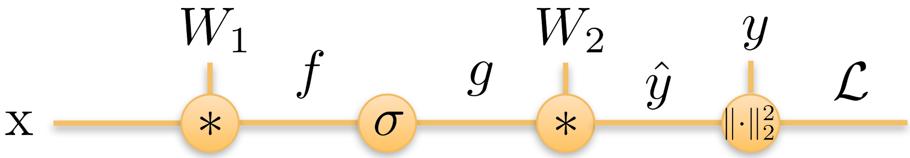
$$\boxed{\frac{\partial h}{\partial f} = \begin{bmatrix} \frac{\partial h_1}{\partial f_1} & \cdots & \frac{\partial h_n}{\partial f_1} \\ \vdots & \ddots & \vdots \\ \frac{\partial h_1}{\partial f_n} & \cdots & \frac{\partial h_n}{\partial f_n} \end{bmatrix}}$$

$$\frac{\partial h}{\partial f} = \begin{bmatrix} g_1 & & 0 \\ & \ddots & \\ 0 & & g_n \end{bmatrix} = \text{diag}(g)$$

Recap: vector differentiation

Final hint: dimensions should always match up!



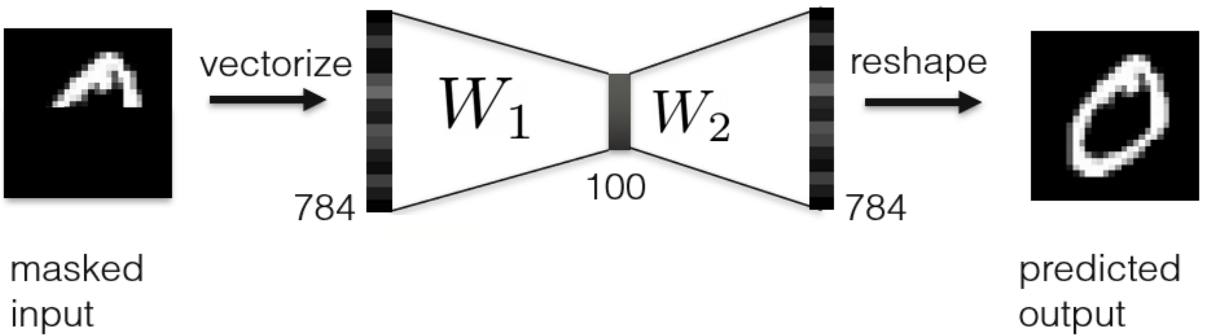
$$\frac{\partial \mathcal{L}}{\partial W_1} = \frac{\partial f}{\partial W_1}\frac{\partial g}{\partial f}\frac{\partial \hat{y}}{\partial g}\frac{\partial \mathcal{L}}{\partial \hat{y}}$$

You should be able to calculate derivatives of each of these terms and then perform matrix multiplications without issues

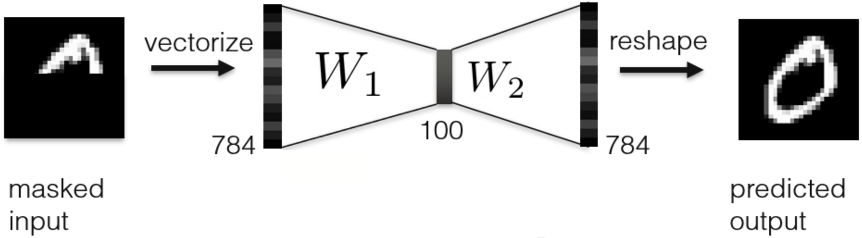
Today

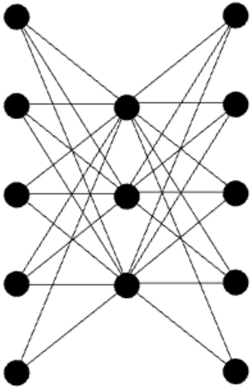
- What is a neural network?
- Training/optimizing neural nets
- Why “neural”?
- Convolutional neural networks
- Applications & inverse problems

Why "neural" network?



Why “neural” network?





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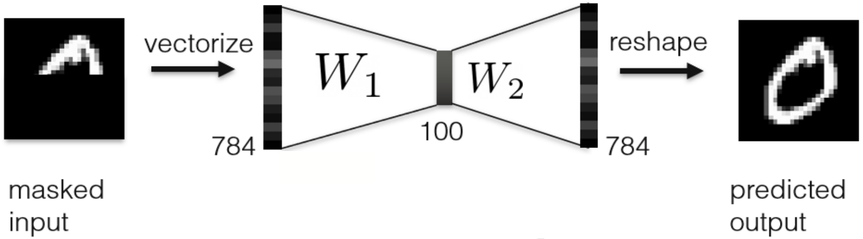

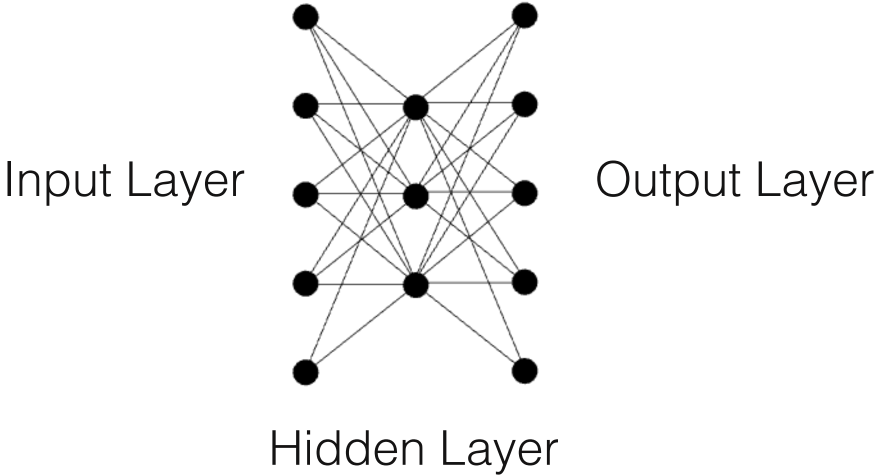

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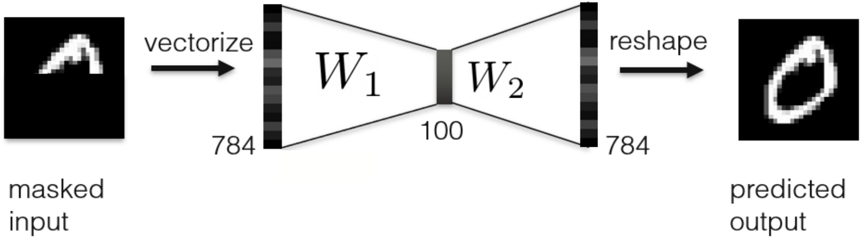
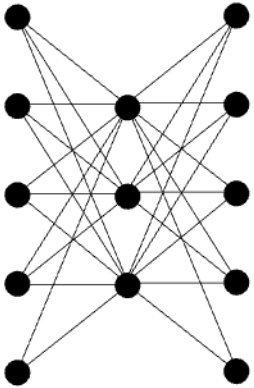


Input Layer

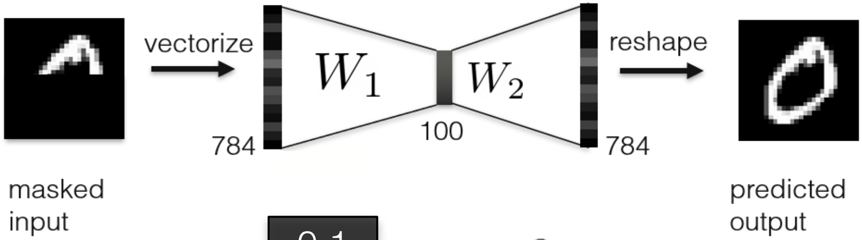


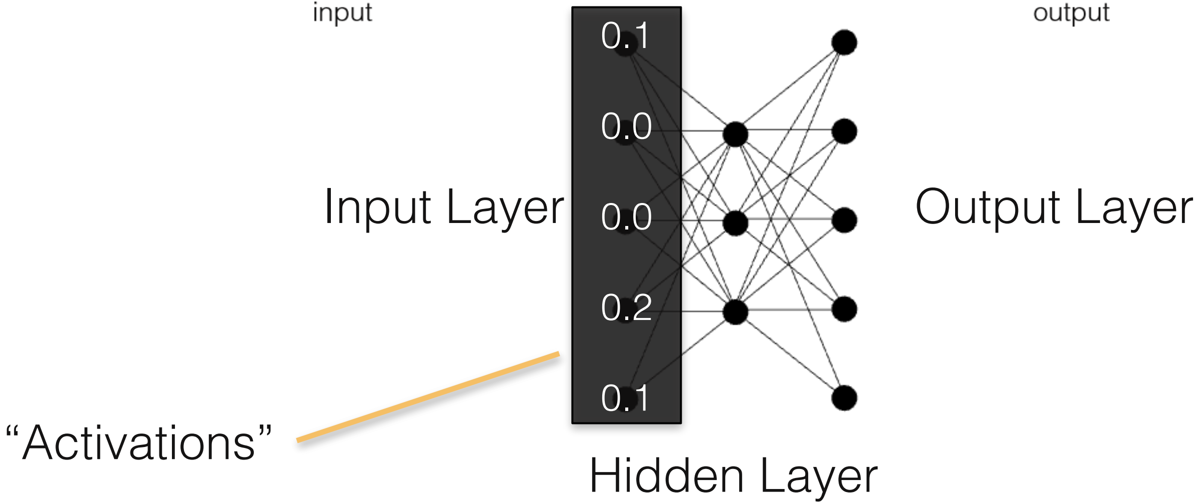
Output Layer

“Neuron”

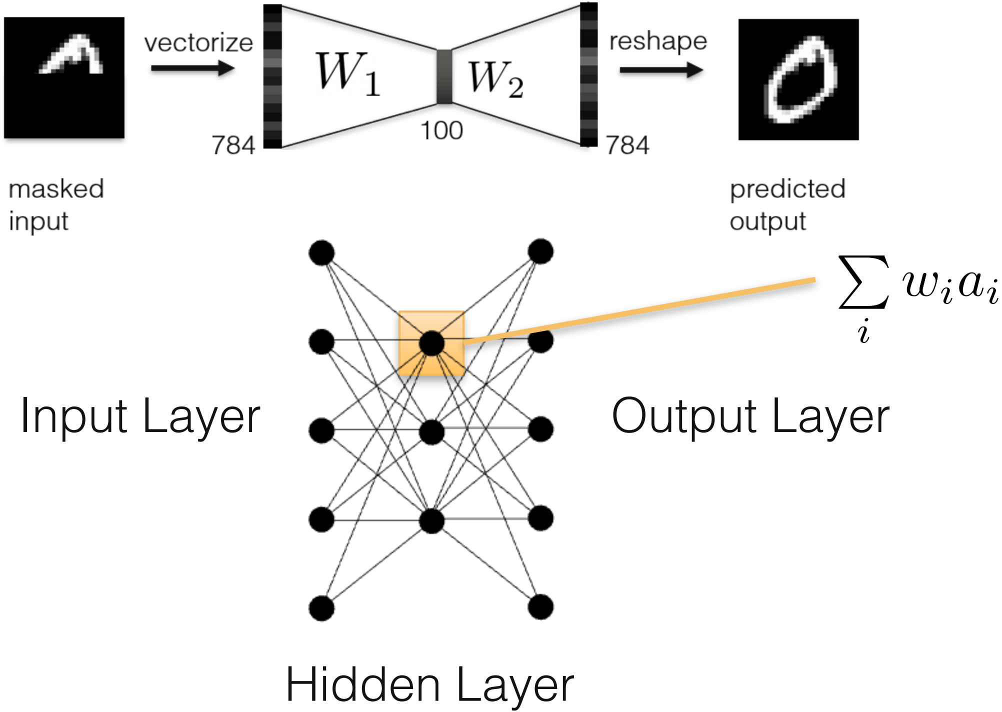
Hidden Layer

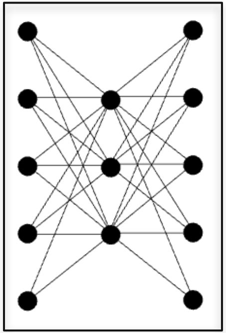
Why “neural” network?

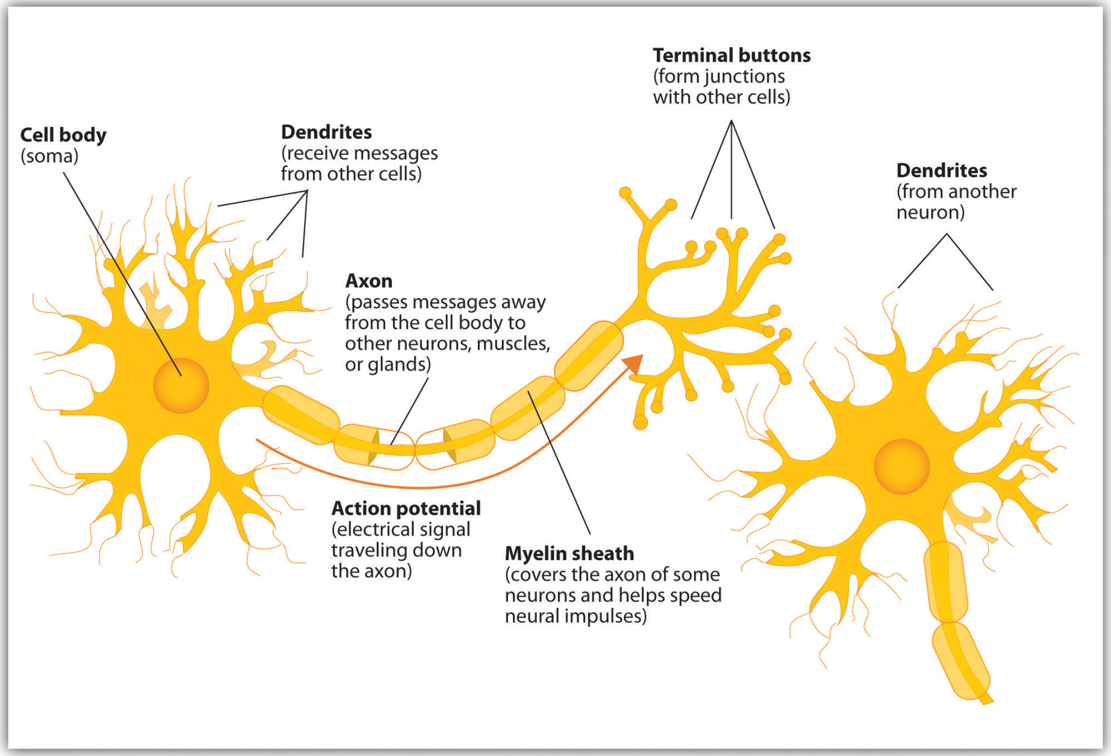




Why “neural” network?





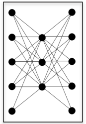

Cell body
(soma)
Dendrites
(receive messages
from other cells)
Terminal buttons
(form junctions
with other cells)
Dendrites
(from another
neuron)
Axon
(passes messages away
from the cell body to
other neurons, muscles,
or glands)
Action potential
(electrical signal
traveling down
the axon)
Myelin sheath
(covers the axon of some
neurons and helps speed
neural impulses)

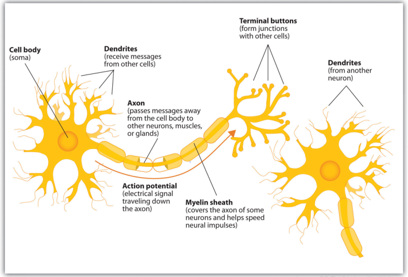
Loose analogy!

- Neurons have activation potentials, all-or-none firing behavior

- Interconnectivity between actual neurons is dense and complicated

- Connection between neurons is complex non-linear dynamical system





Today

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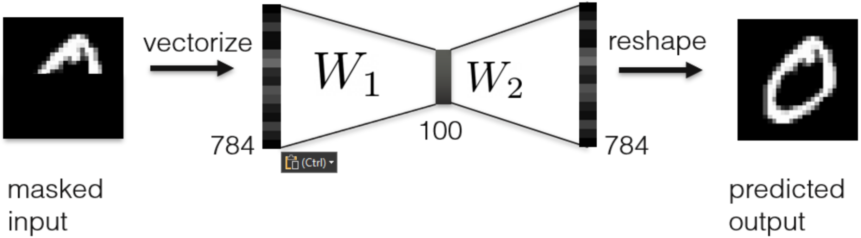
Drawbacks of fully-connected networks



- spatial structure is destroyed
- fully-connected weights do not scale

Convolutional Neural Networks

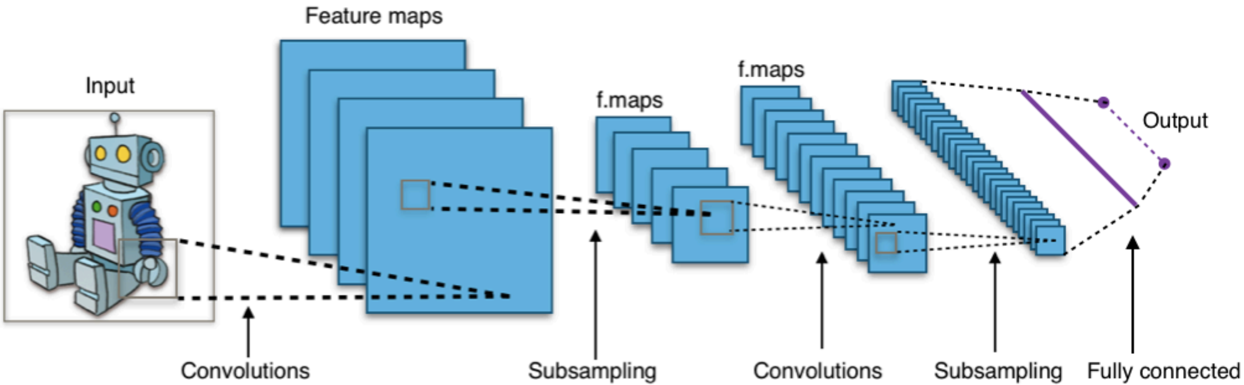


Image: CC Aphex34

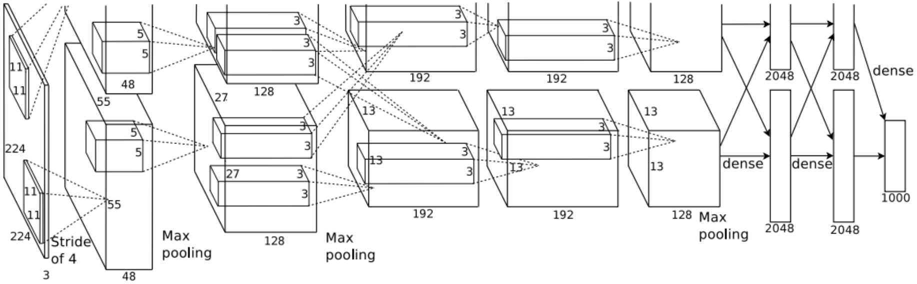
- Exploit spatial structure
- Scale to large inputs with fewer parameters
- Remarkable performance for processing visual data

AlexNet & surge in popularity

2010: ImageNet Large Scale Visual Recognition Challenge

- 10 million labeled images

First convolutional network for image classification



AlexNet [Krizhevsky '12]

AlexNet & surge in popularity

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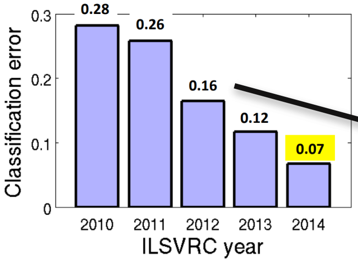
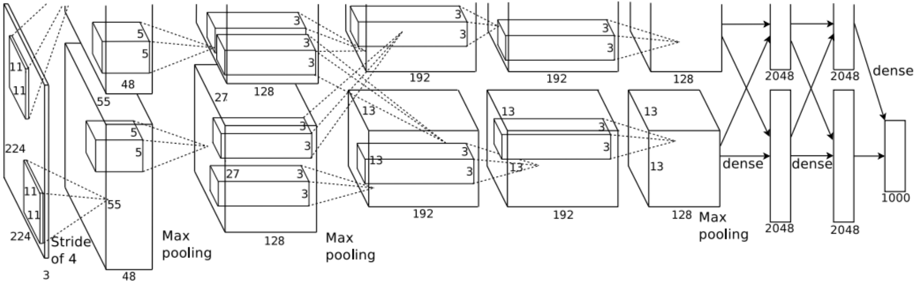


[Russakovsky ’15]



AlexNet [Krizhevsky ‘12]

CNNs

AlexNet & surge in popularity

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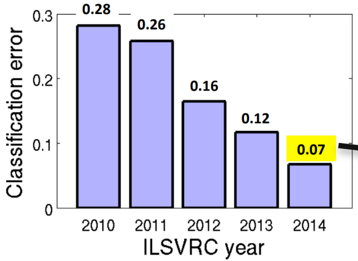
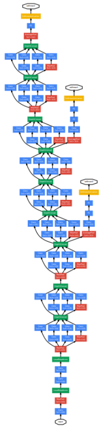
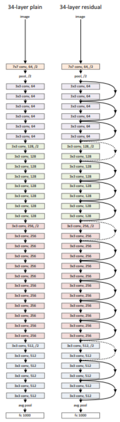


[Russakovsky '15]

Deep networks





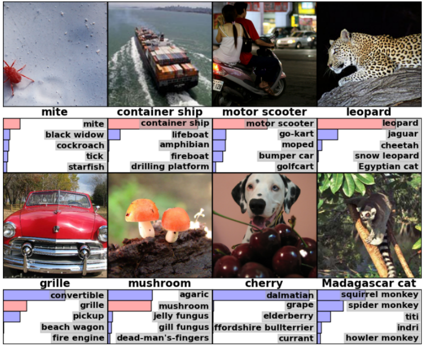
VGG [Simonyan '14]

GoogLeNet [Szegedy '14]

ResNet [He '15]

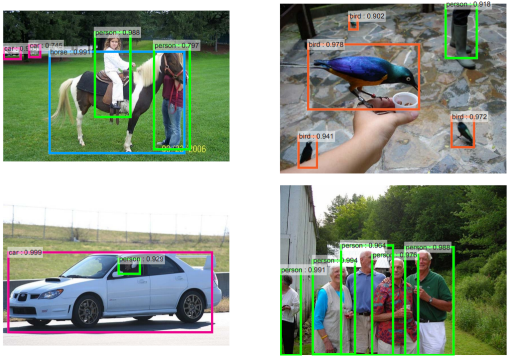
Image Classification

[Krizhevsky '12]



Object Detection

[Ren '16]

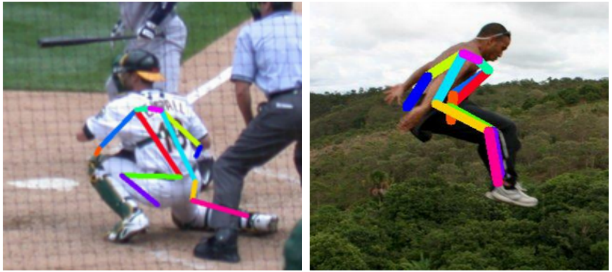


Segmentation

[Farabet '13]

Pose estimation

[Toshev '14]



Imaging & Image processing

Image Denoising

[Zhang '17]

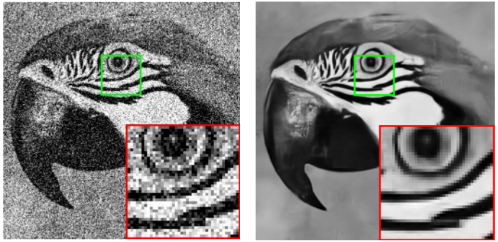


Image Deblurring

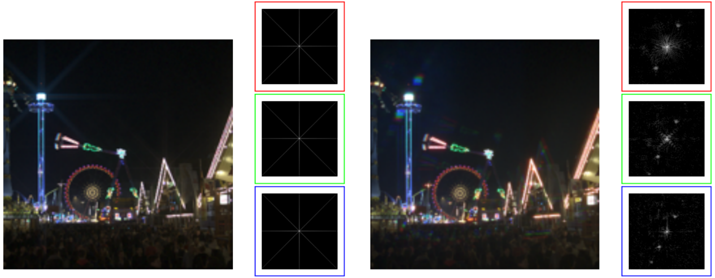
[Nah '17]

Learned ISPs

[Chen '18]

End-to-End Optimization

[Metzler '19]



Imaging & Image processing

Monocular Depth Estimation

[Eigen '14]

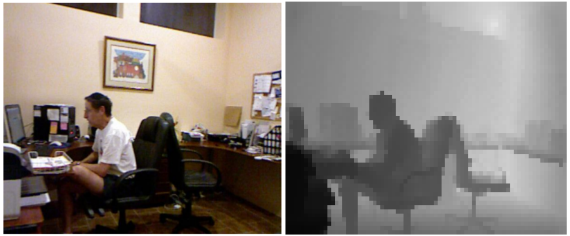
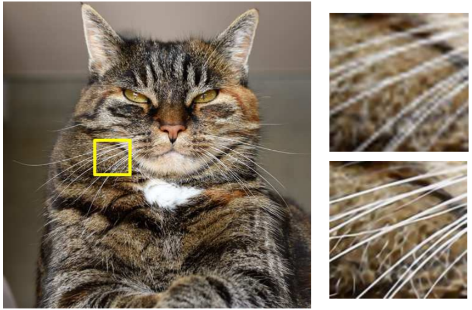


Image Relighting

[Sun '19]

Image Super-resolution

[Lim '17]



Synthetic Depth-of-Field

ai.googleblog.com

Fully-Connected Layer

1

3072

Vectorized Image

$$Wx$$

weights 100 x 3072

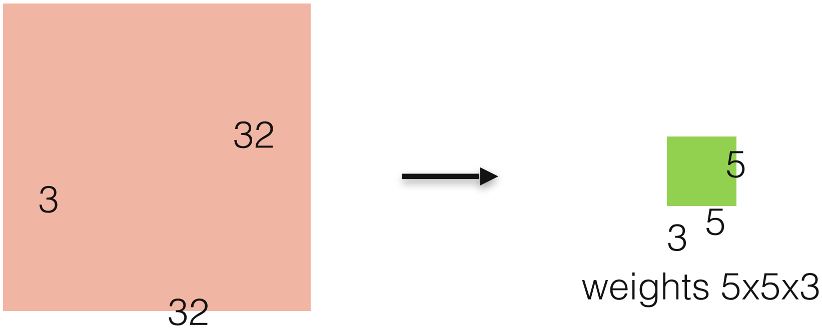
Weight Matrix

1

100

Output Activation

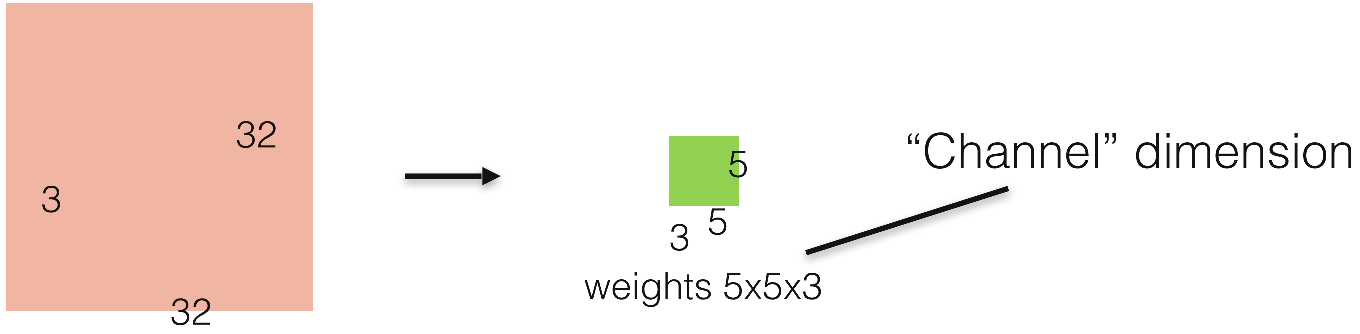
Convolutional Layer



Input Image

Filter

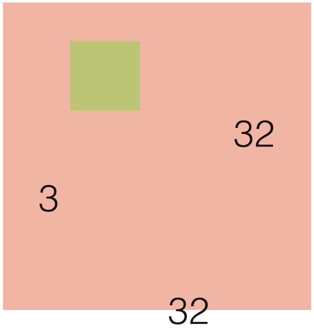
Convolutional Layer



Input Image

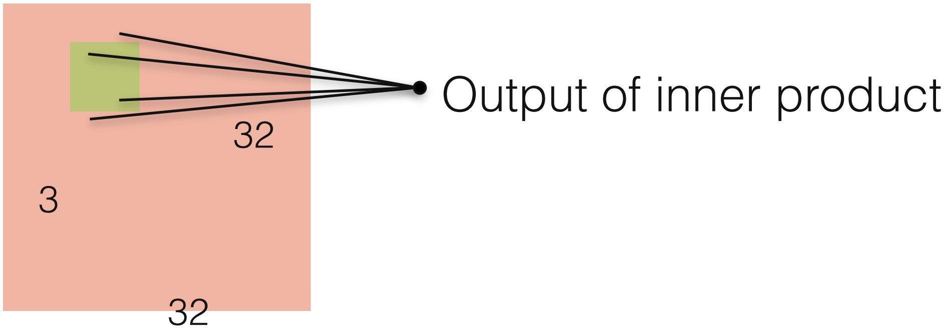
Filter

Convolutional Layer



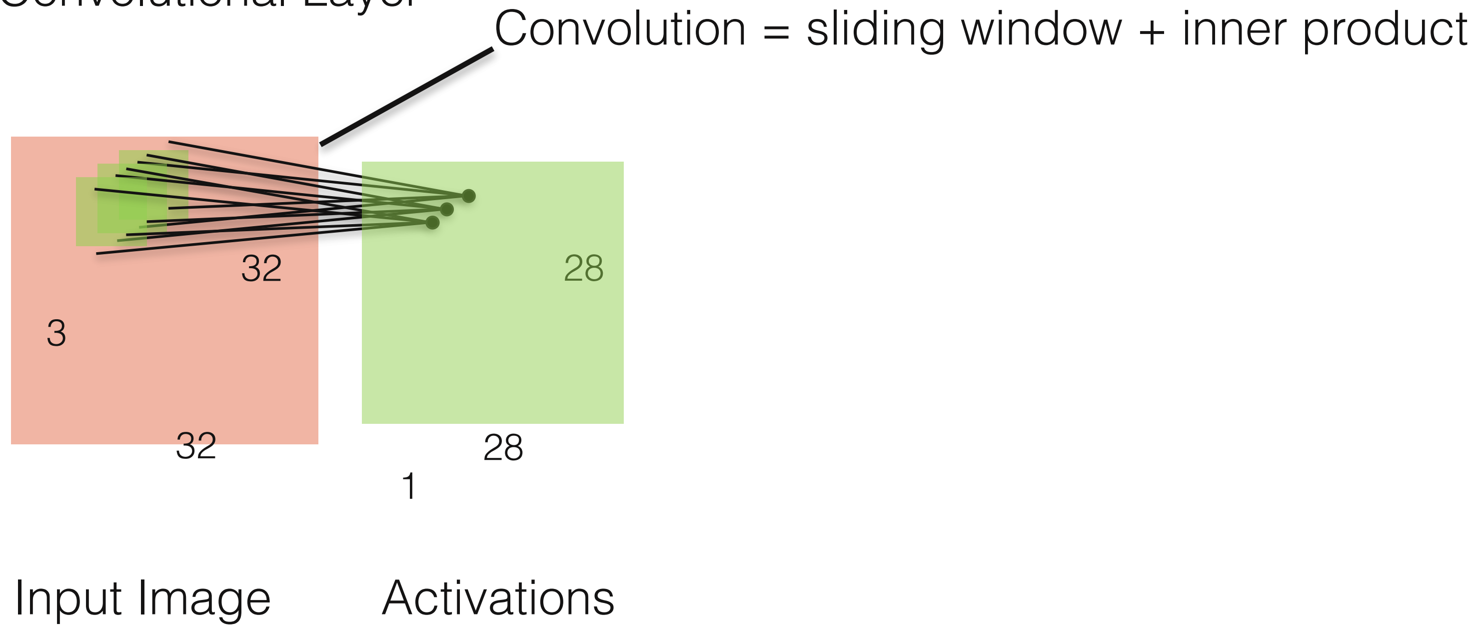
Input Image

Convolutional Layer

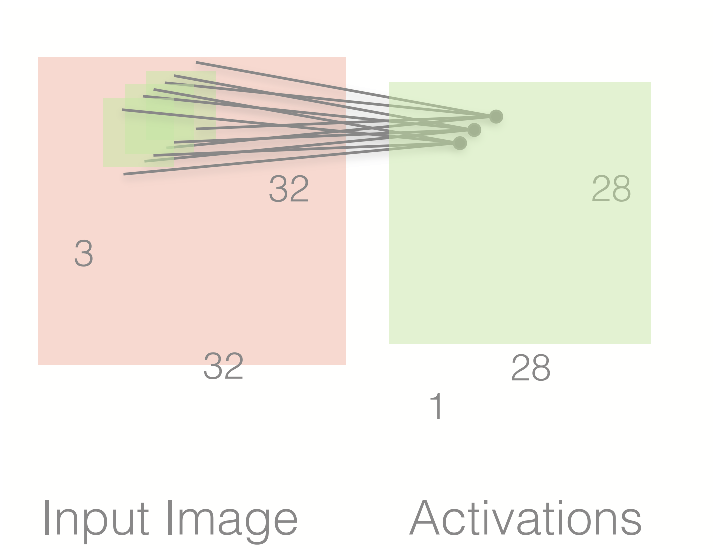


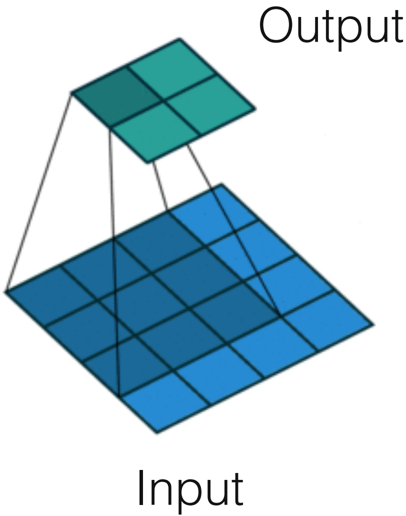
Input Image

Convolutional Layer



Convolutional Layer

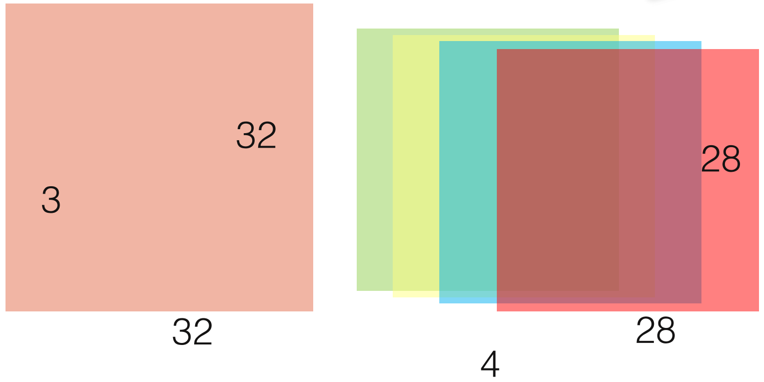




https://github.com/vdumoulin/conv_arithmetic

Convolutional Layer

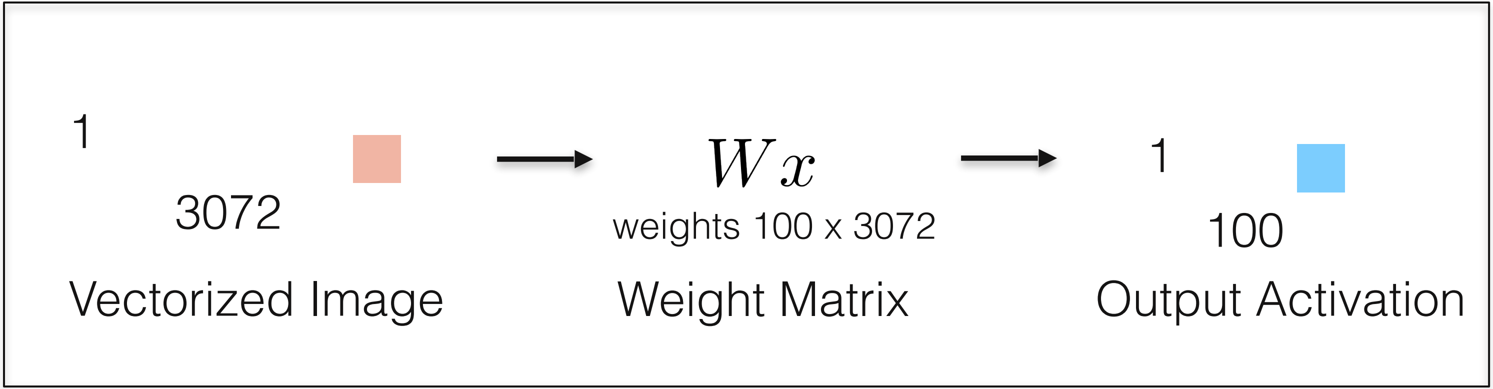
Multiple output channels using multiple filters



Input Image

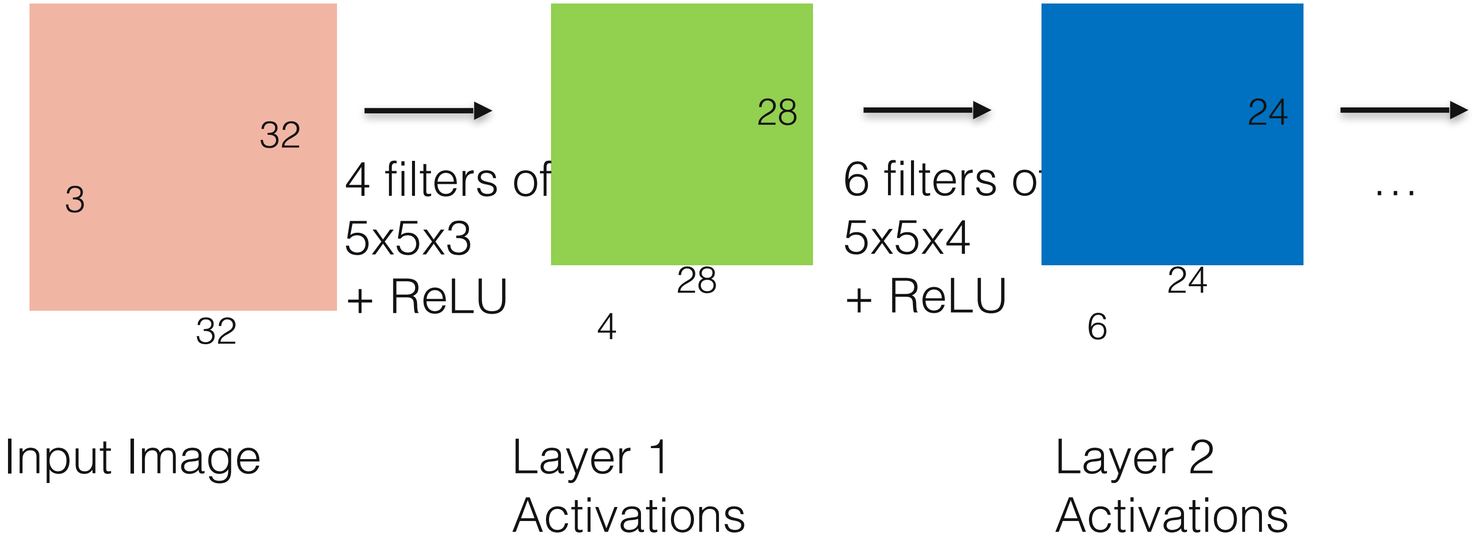
Activations

Fully-Connected Layer



Special case of convolutional layer when filter size = input size!

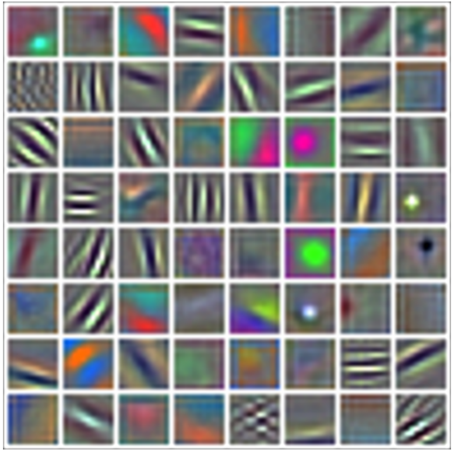
Convolutional Neural Network



Case Study: AlexNet

Input Image

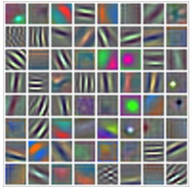
First-layer Filters

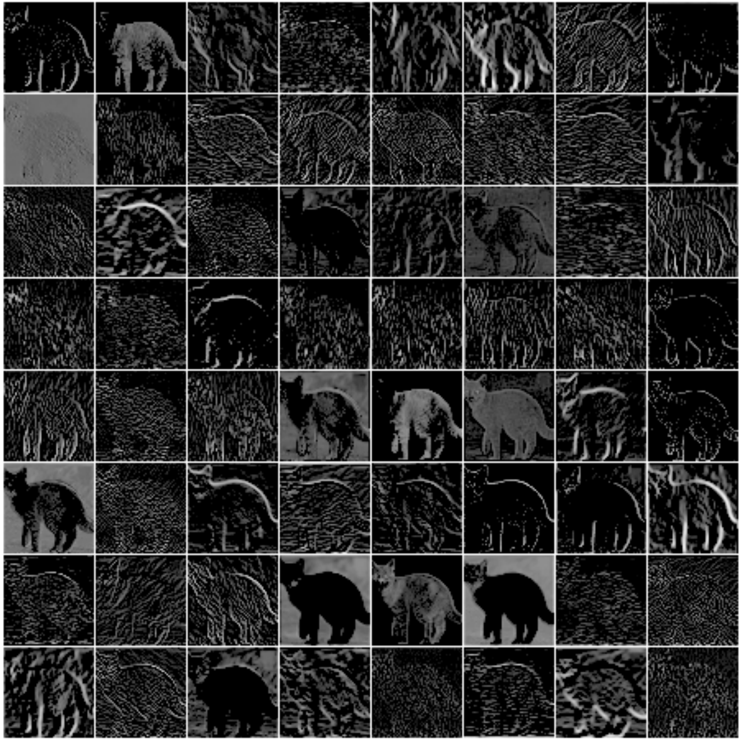


Case Study: AlexNet

Input Image

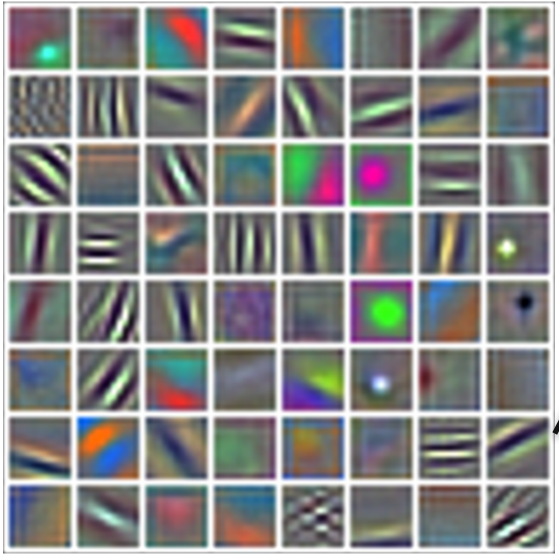
First-layer Filters





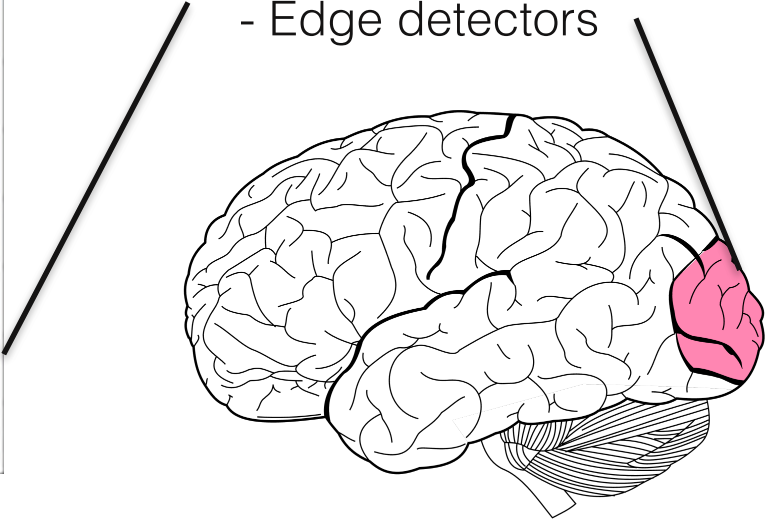
Activations

Case Study: AlexNet



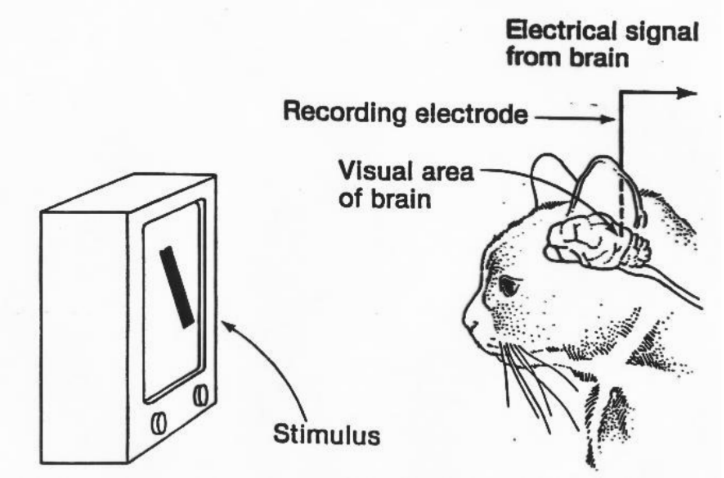
First-layer Filters

Similar to simple cells
in visual cortex!
- Edge detectors



Case Study: AlexNet

[Hubel & Wiesel 1959]



Simple cells in visual cortex detect edges, complex cells compose earlier responses

CNN higher layer filters

[Olah ‘17]

Dataset examples that maximize neuron outputs

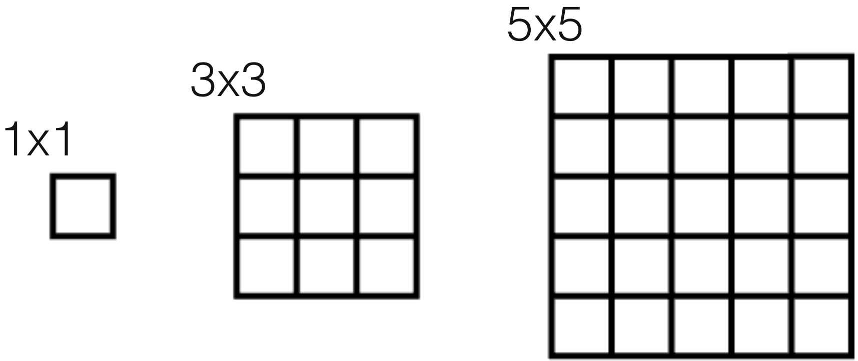
CNN Building Blocks

Design choices:
- filter size
- number of filters
- padding
- stride

Layer types:
- pooling
- transpose convolutions
- upsampling layers

CNN Building Blocks

Filter size



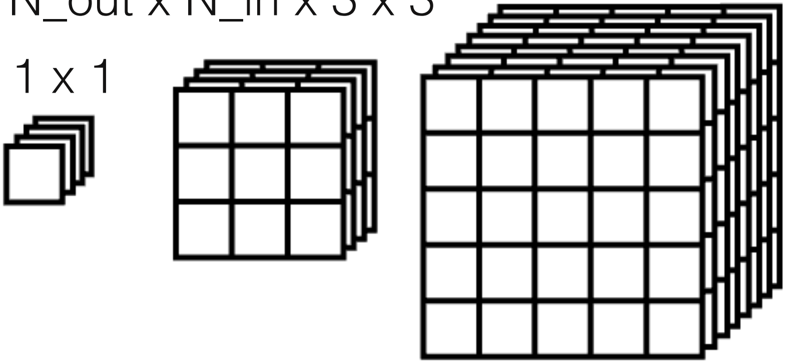
CNN Building Blocks

Number of channels

N_out x N_in x 5 x 5

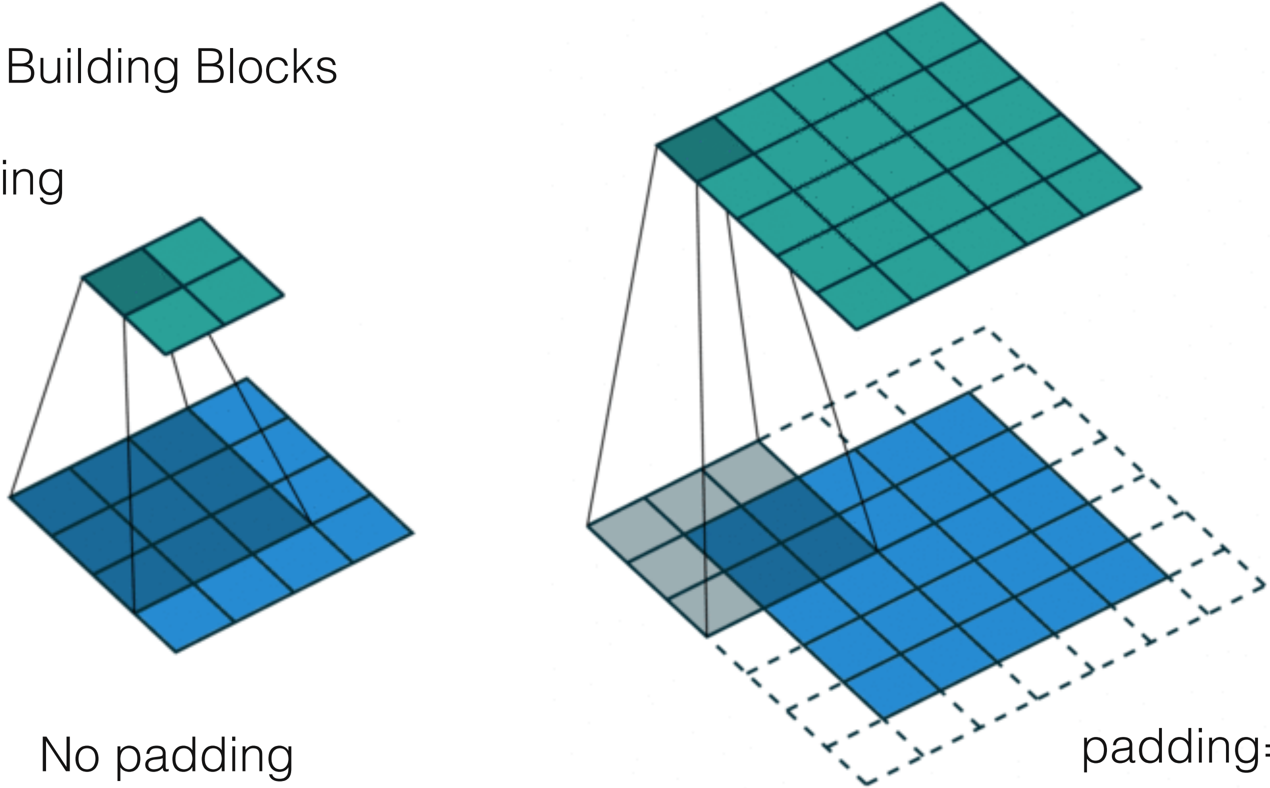
N_out x N_in x 3 x 3

N_out x N_in x 1 x 1



CNN Building Blocks

padding



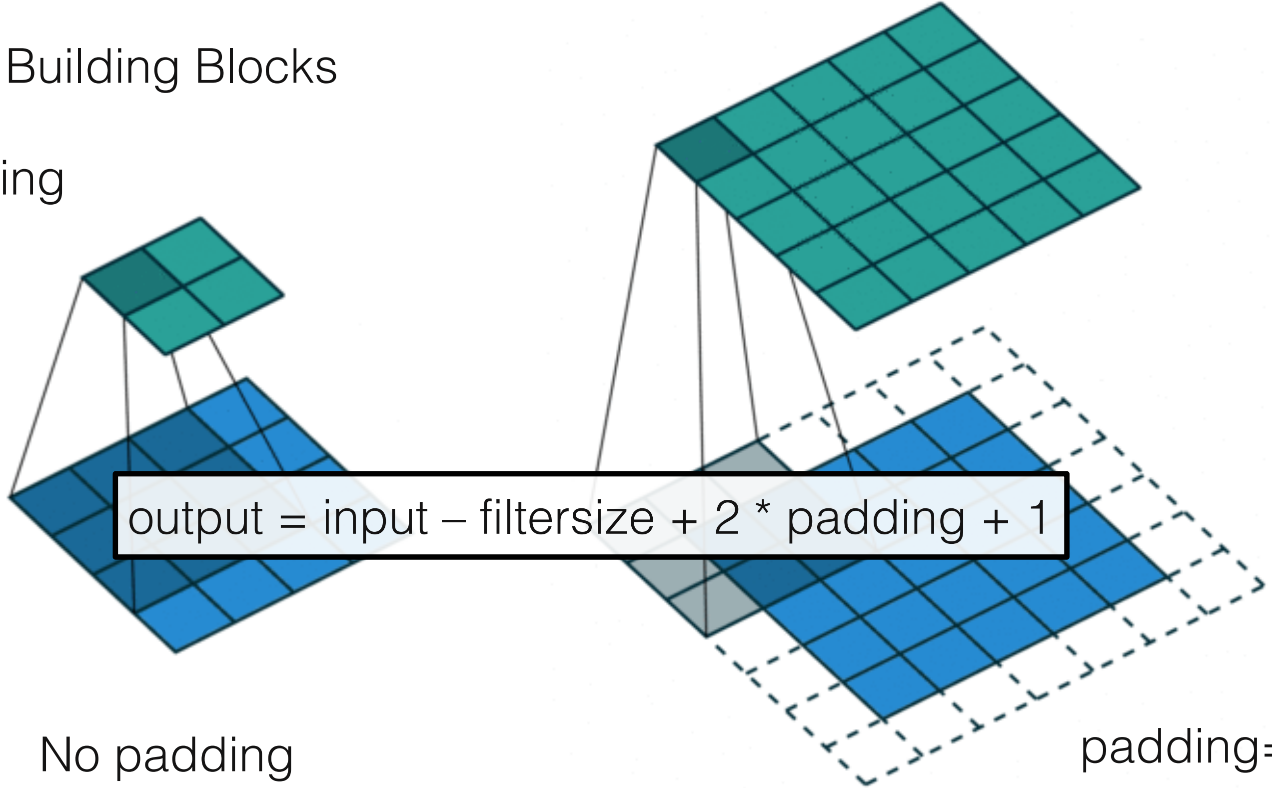
No padding

padding=1

https://github.com/vdumoulin/conv_arithmetic

CNN Building Blocks

padding



$$\text{output} = \text{input} - \text{filtersize} + 2 * \text{padding} + 1$$

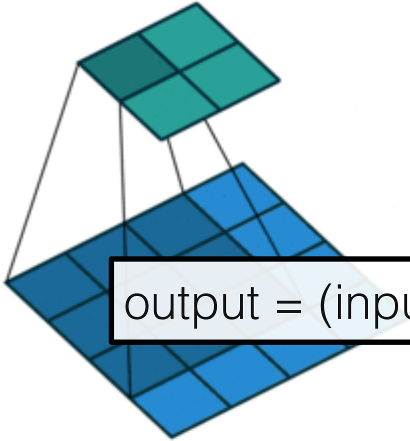
No padding

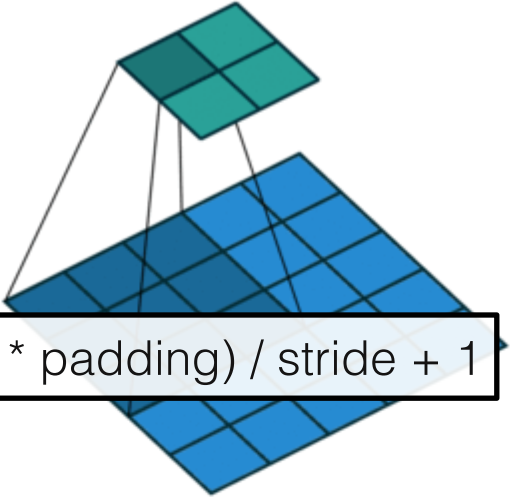
padding=1

https://github.com/vdumoulin/conv_arithmetic

CNN Building Blocks

stride





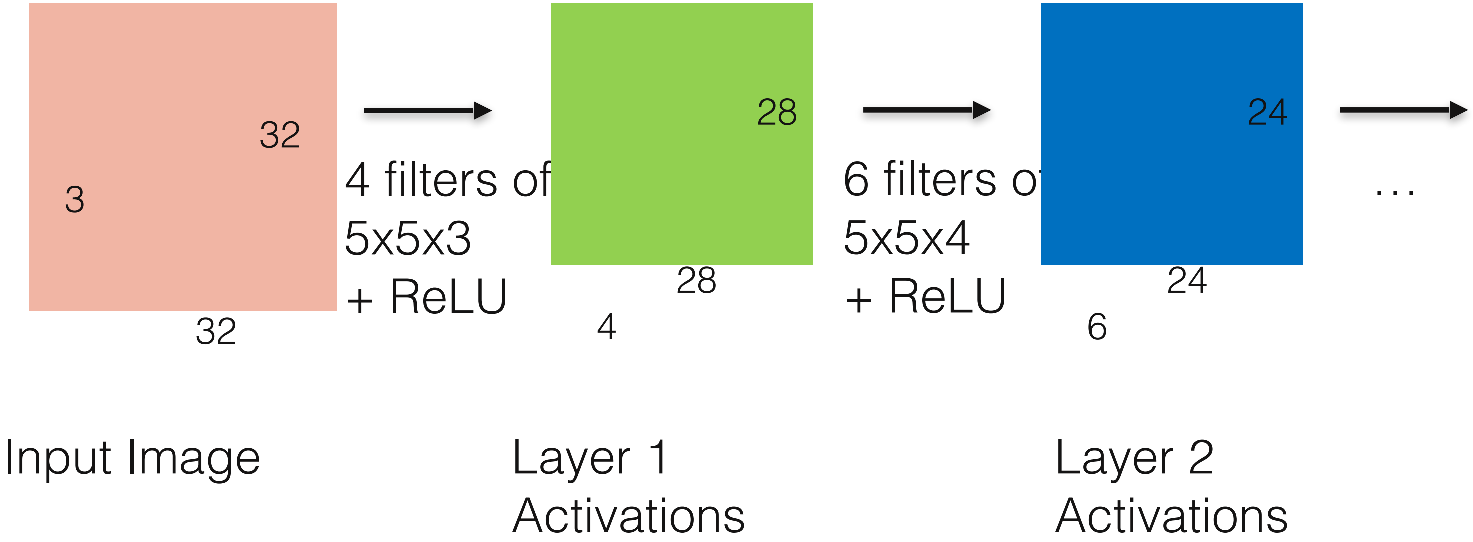
output = (input – filtersize + 2 * padding) / stride + 1

stride = 1

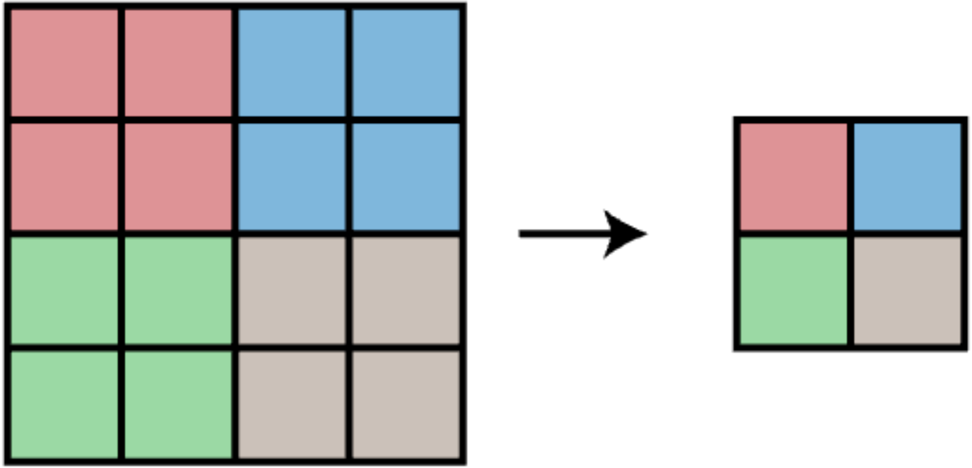
stride = 2

https://github.com/vdumoulin/conv_arithmetic

Convolutional Neural Network

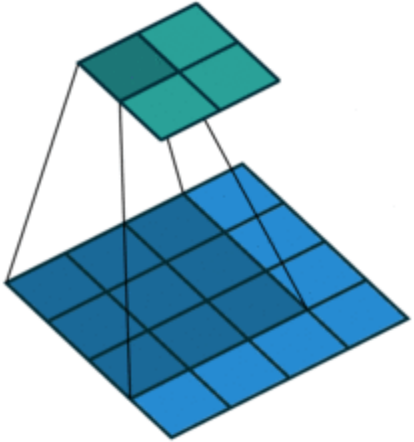


Layer types: Pooling

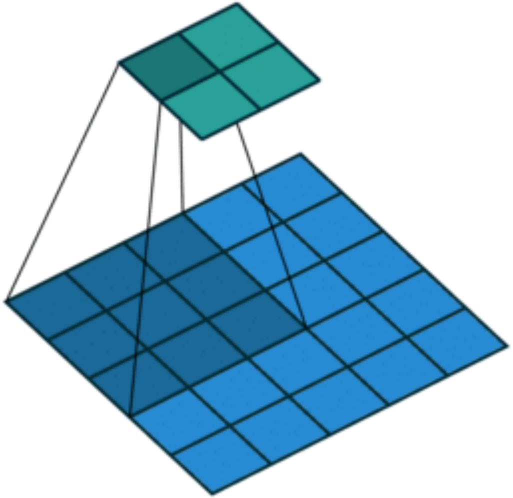


e.g., max pool size=2, stride=2

Transpose Convolution



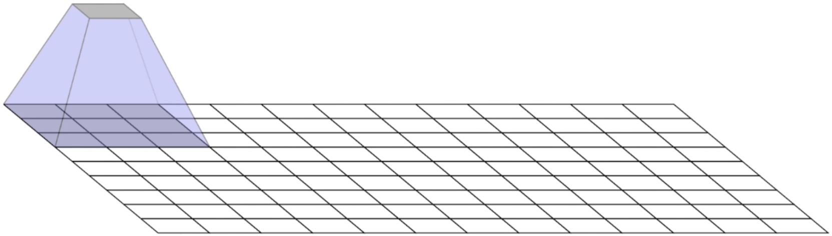
stride=1

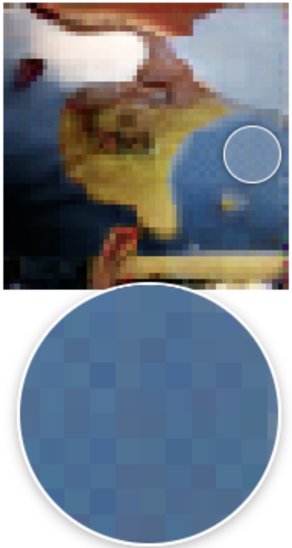


stride=2

https://github.com/vdumoulin/conv_arithmetic

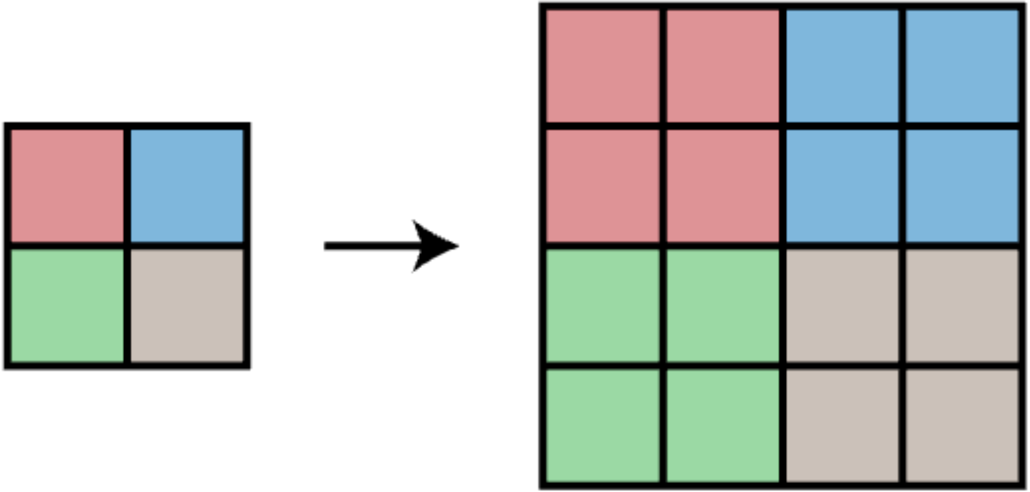
Transpose Convolution (checkerboard artifacts)





[Odena '16]

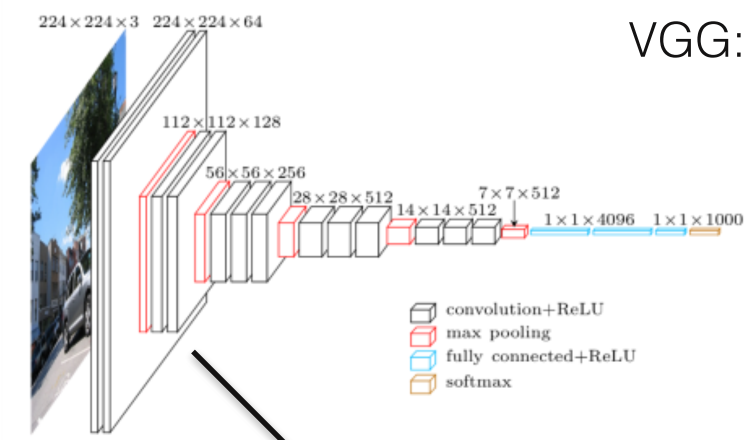
Upsampling layers



e.g., bilinear upsampling, nearest neighbor upsampling

Common Network Architectures

VGG: one of the first "deep" CNNs

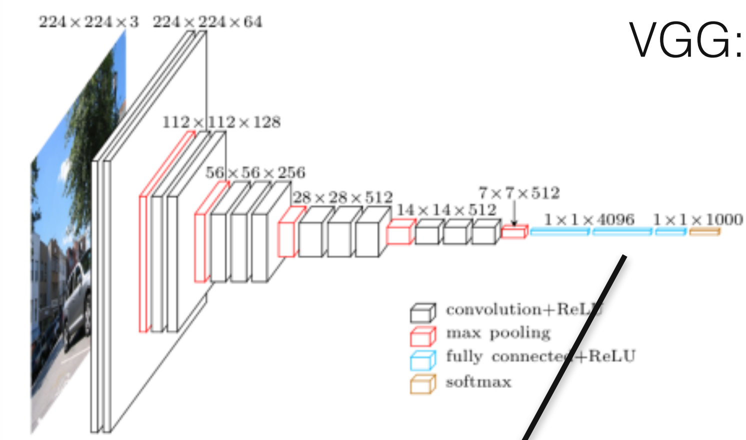


downsampling with max pooling

Image: Davi Frossard

Common Network Architectures

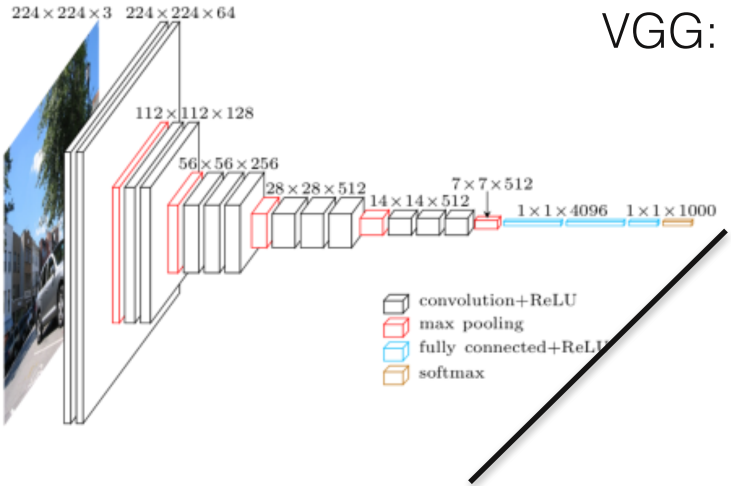
VGG: one of the first "deep" CNNs



Classification scores output with fully-connected layers

Image: Davi Frossard

Common Network Architectures



VGG: one of the first “deep” CNNs

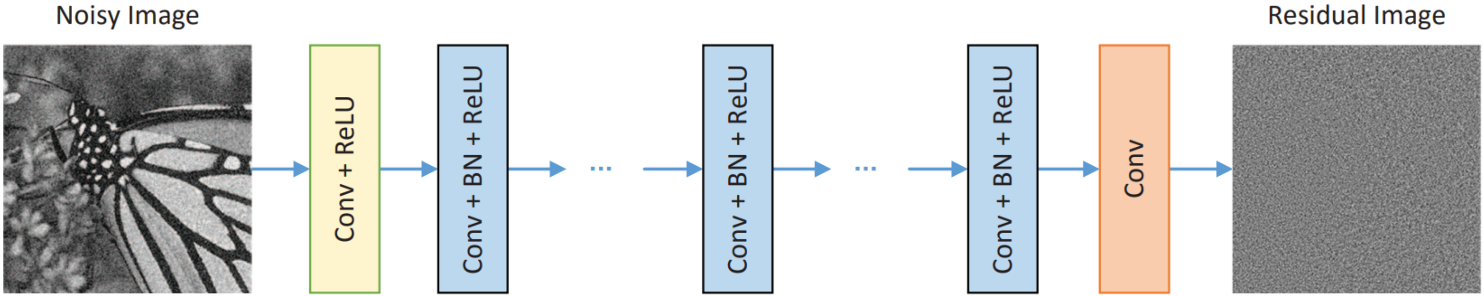
Not suitable for image processing…

Image: Davi Frossard

Today

- What is a neural network?
- Training/optimizing neural nets
- Why “neural”?
- Convolutional neural networks
- Applications & inverse problems

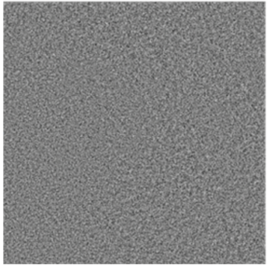
Image denoising with DnCNN



[Zhang '16]

Key ideas: residual learning & batch normalization

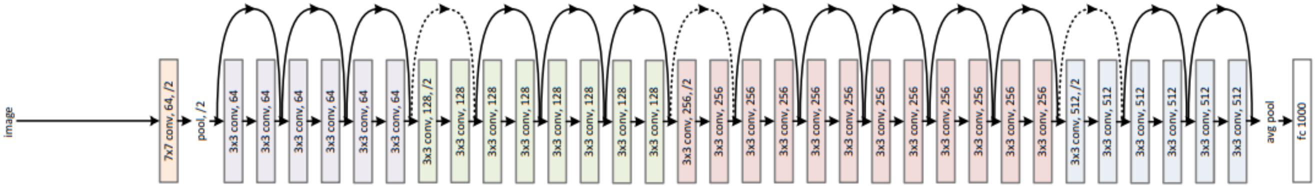
Residual Learning

Clean image = noisy image - estimated noise

[Zhang ‘16]

Residual Learning



[He ‘15]

Popularized by residual nets “ResNets” for image classification

- Usually easier to optimize
- Better classification accuracy, good for many tasks!

Batch Normalization

Normalizes layer activations to zero mean, unit variance, preventing distribution shifts during training

- can speed up and stabilize training
- seems to smooth out loss landscape

BATCHNORM2D

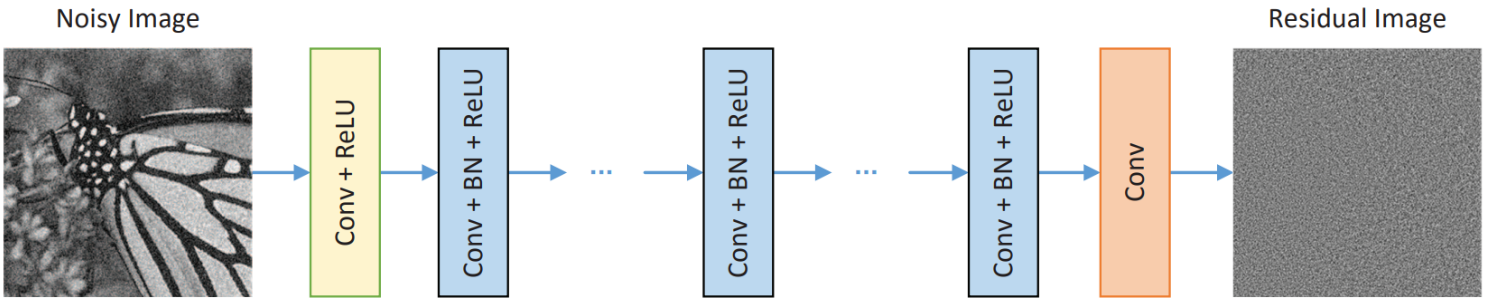
CLASS `torch.nn.BatchNorm2d(num_features, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True, device=None, dtype=None)` [SOURCE]

Applies Batch Normalization over a 4D input (a mini-batch of 2D inputs with additional channel dimension) as described in the paper Batch Normalization: Accelerating Deep Network Training by Reducing Internal Covariate Shift .

$$y = \frac{x - \mathrm{E}[x]}{\sqrt{\mathrm{Var}[x] + \epsilon}} * \gamma + \beta$$

https://pytorch.org/docs/stable/generated/torch.nn.BatchNorm2d.html

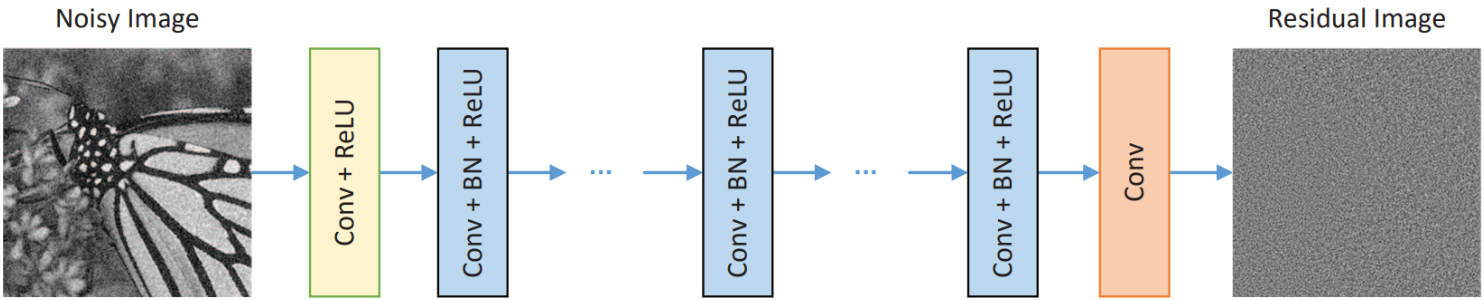
Image denoising with DnCNN



[Zhang '16]

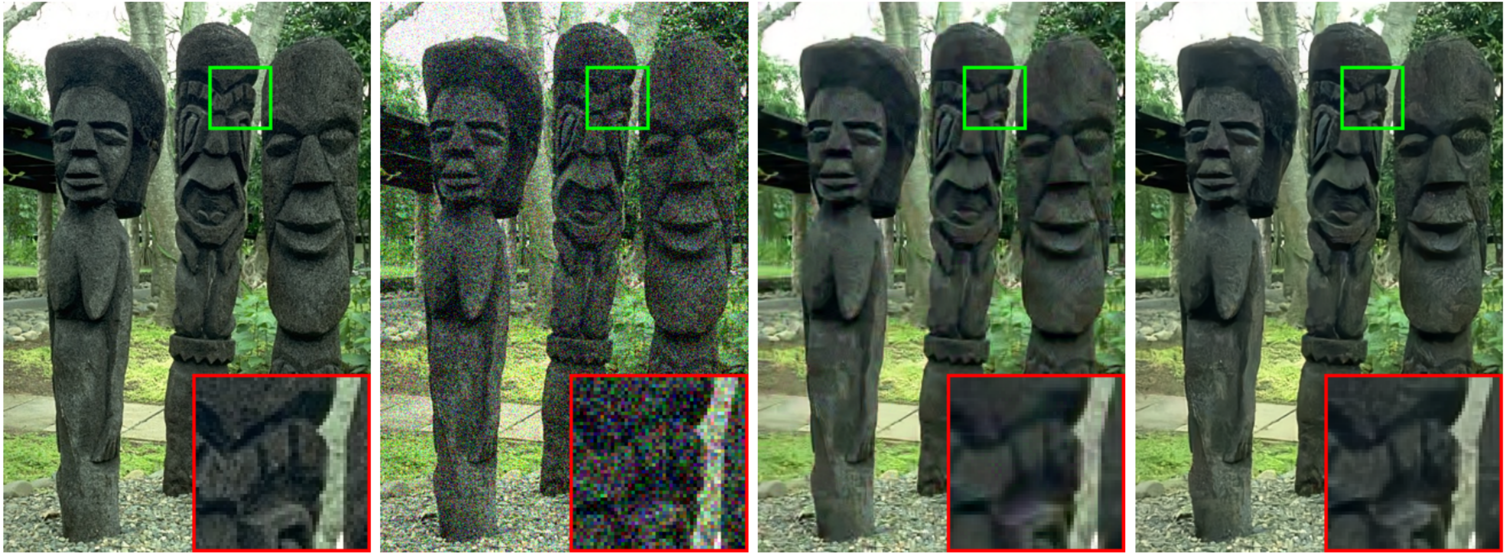
(Remember to disable the bias in your conv layer)

Image denoising with DnCNN



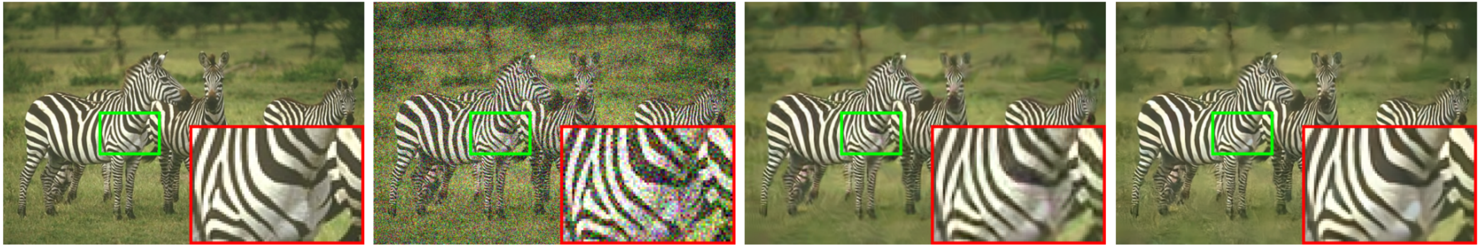
[Zhang '16]

No fully connected layers – can be applied to any input size



(a) Ground-truth (b) Noisy / 17.25dB (c) CBM3D / 25.93dB (d) CDnCNN-B / 26.58dB

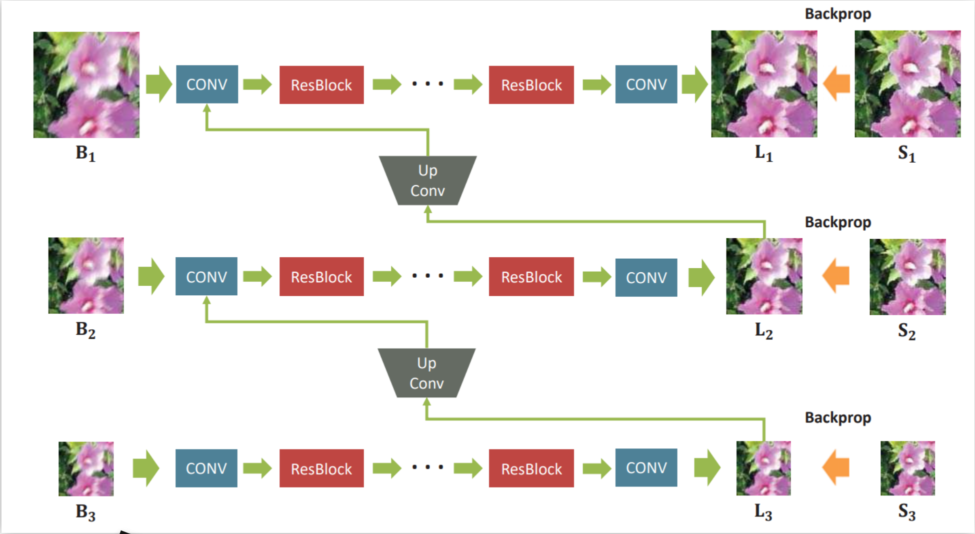
[Zhang ‘16]



(a) Ground-truth (b) Noisy / 15.07dB (c) CBM3D / 26.97dB (d) CDnCNN-B / 27.87dB

[Zhang ‘16]

Multi-Scale Architectures



Uses image pyramid to process & deblur

[Nah '18]

Multi-Scale Architectures

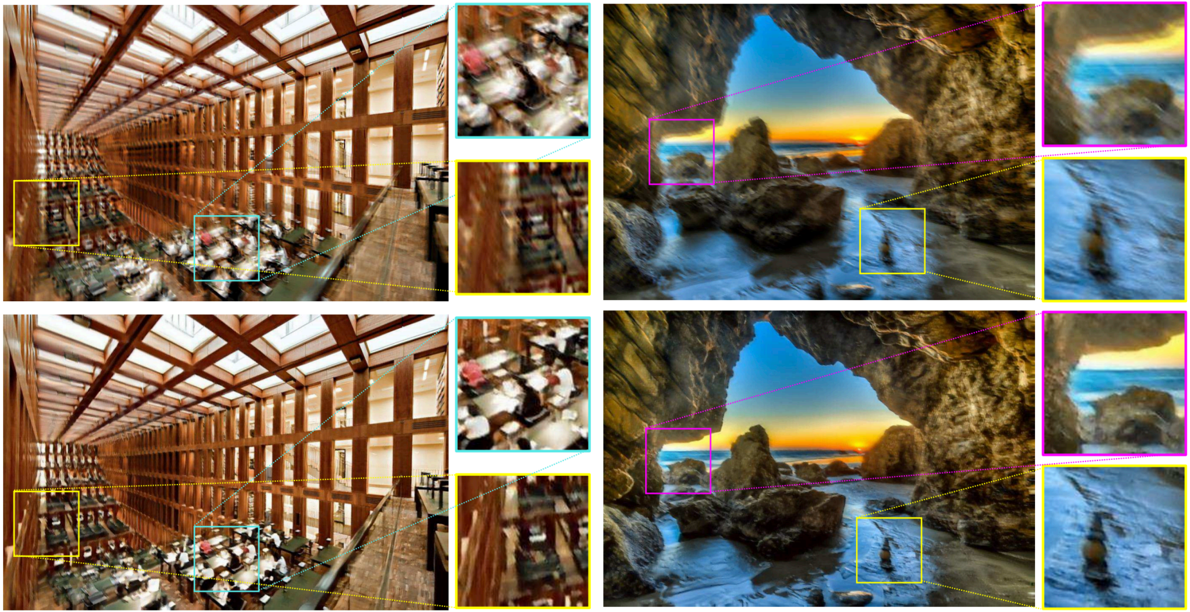
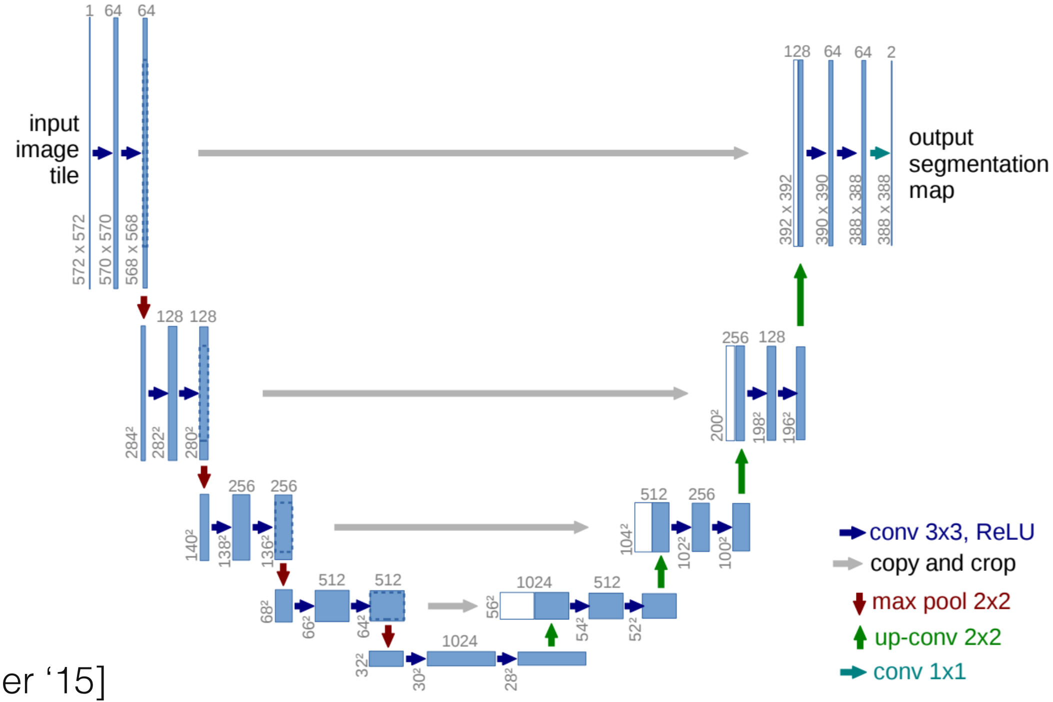


Figure 6. Deblurring results on the dataset [20]. The top row shows results of results of Sun et al. [26] and the bottom row shows our results.

[Nah '18]

U-Net: General-purpose architecture

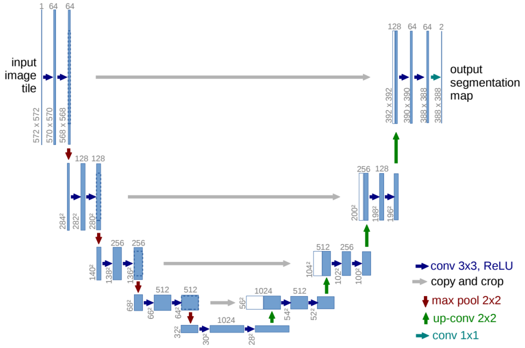


[Ronneberger '15]

U-Net: General-purpose architecture

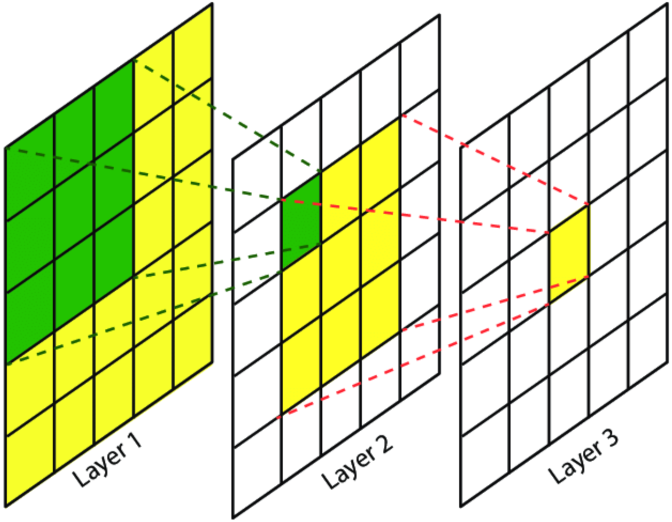
Introduced for biomedical image segmentation

- Uses residual connections
- Multi-scale processing (captures details at different scales)
- Large receptive field!



U-Net: General-purpose architecture

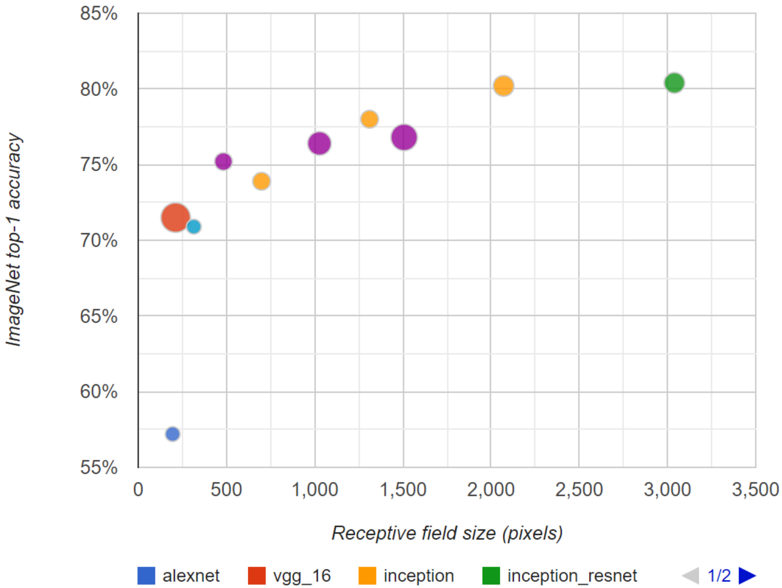
Receptive field: size of the input that contributes to the activation/ output value



[Lin '17]

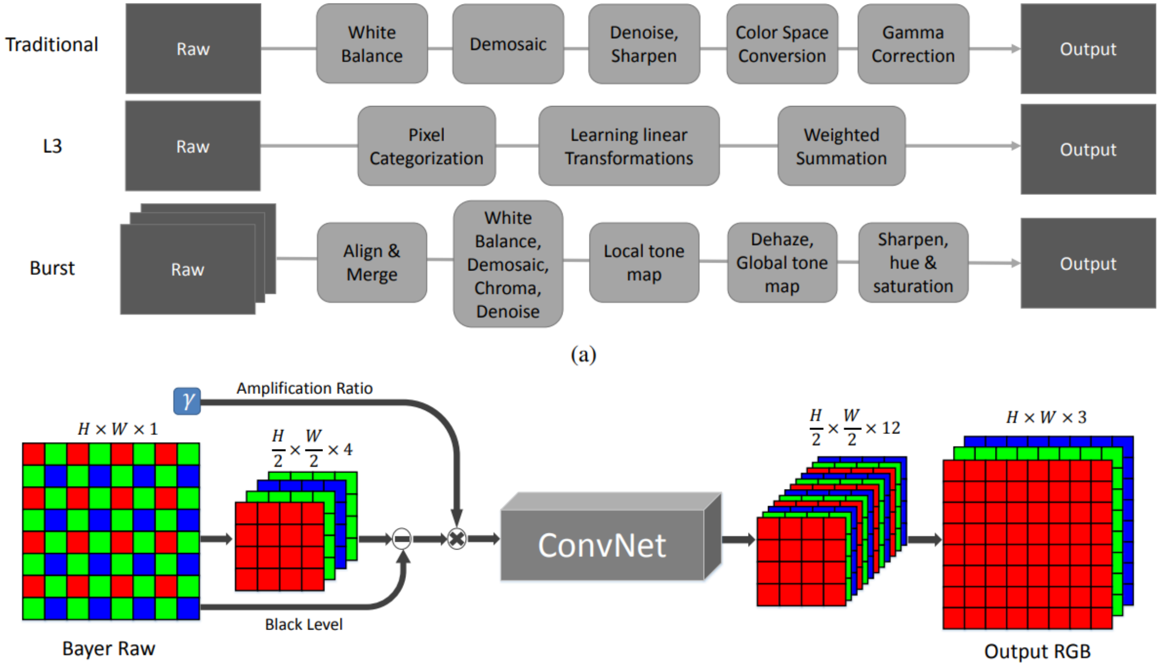
U-Net: General-purpose architecture

Large receptive field is important for high-level vision tasks and semantic understanding



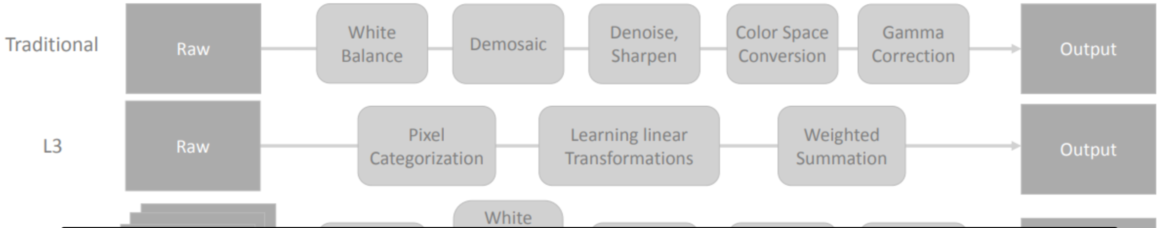
[Araujo '19]

Learned ISP

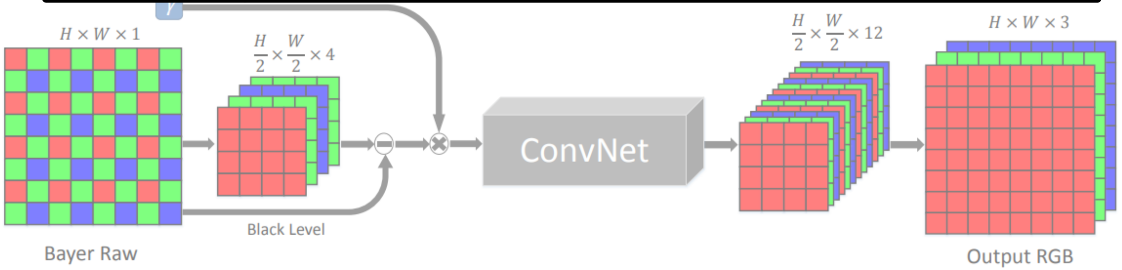


[Chen '18]

Learned ISP

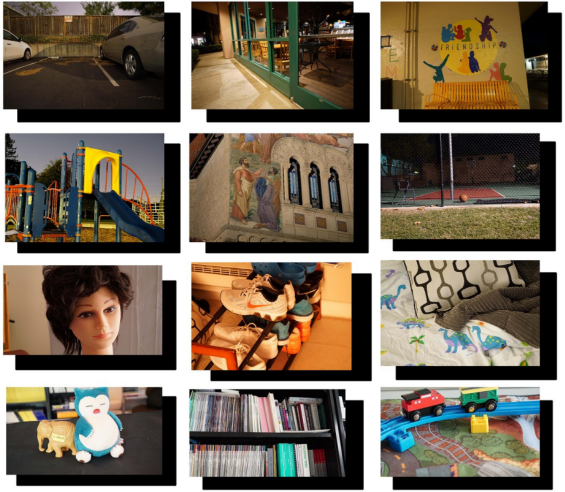


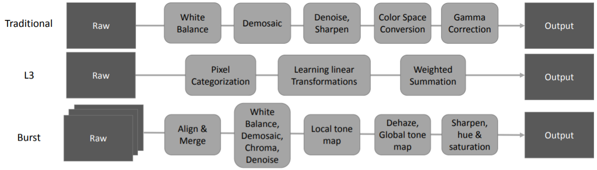
fully-connected layers that require processing small image patches and reassembling them [26]. Our default architecture is the U-net [35].



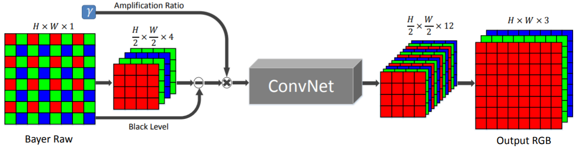
[Chen '18]

Learned ISP





(a)

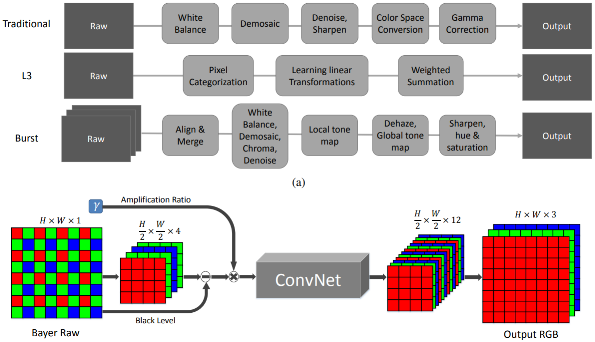


Trained on short-exposure (noisy) / long-exposure image pairs

[Chen '18]

Learned ISP

(a) Traditional pipeline (b) Our result



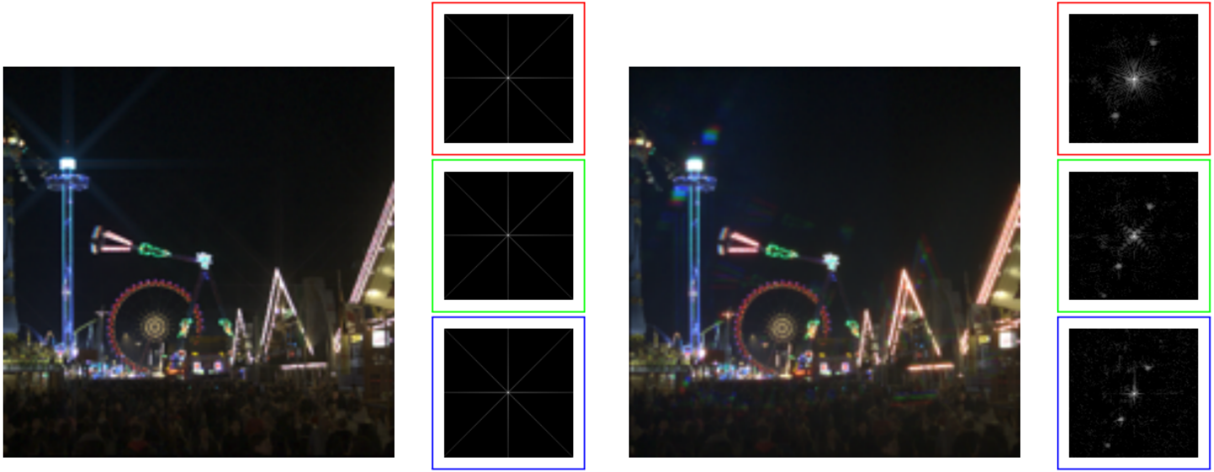
[Chen '18]

Deep optics for HDR imaging

What kind of PSF would be good for HDR imaging?

- Should preserve fine details
- Should help to avoid saturation

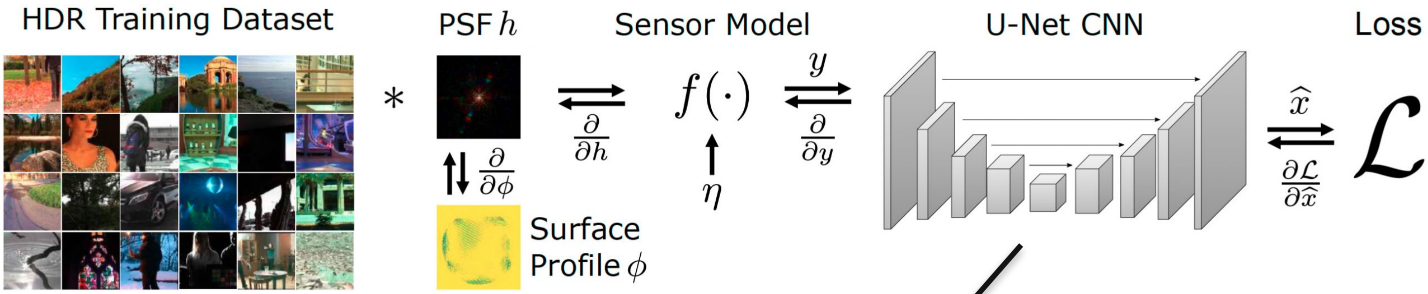
Deep optics for HDR imaging



(a) Star PSF (b) E2E PSF

[Metzler '20]

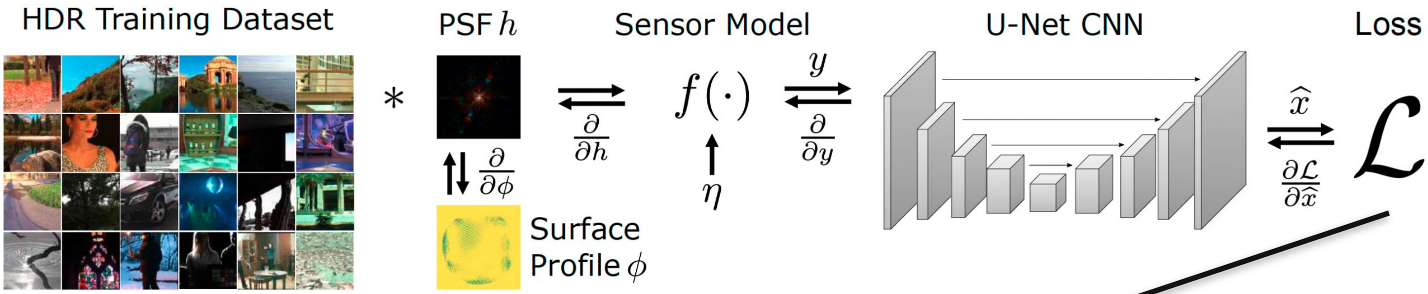
Deep optics for HDR imaging



U-Net again

[Metzler '20]

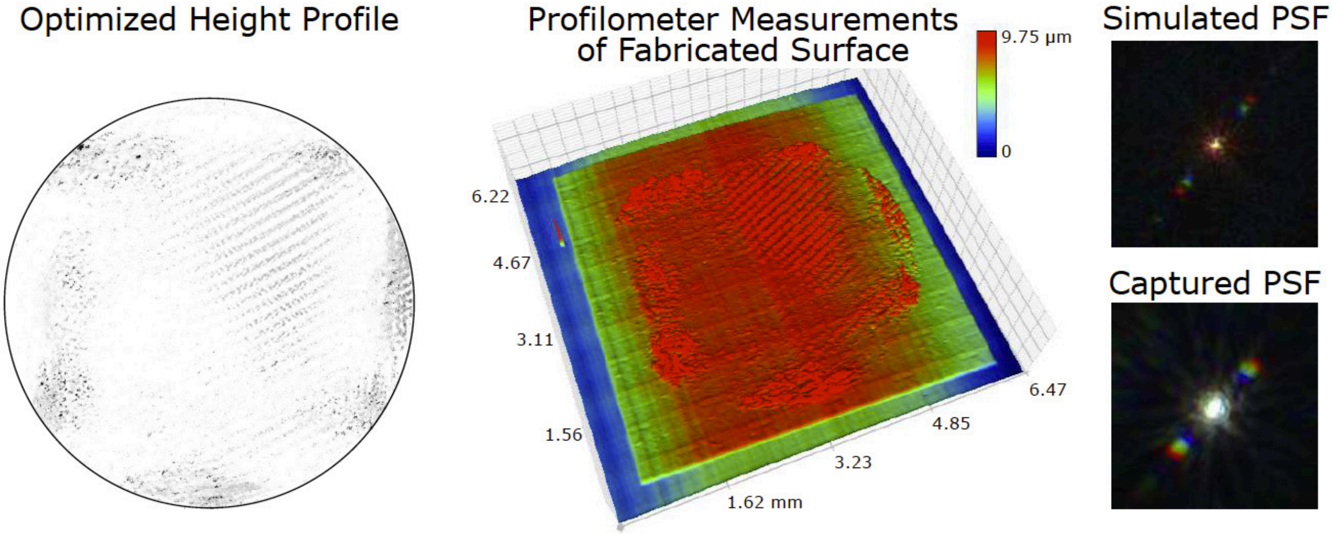
Deep optics for HDR imaging



Minimize difference between reconstruction and tone-mapped GT images

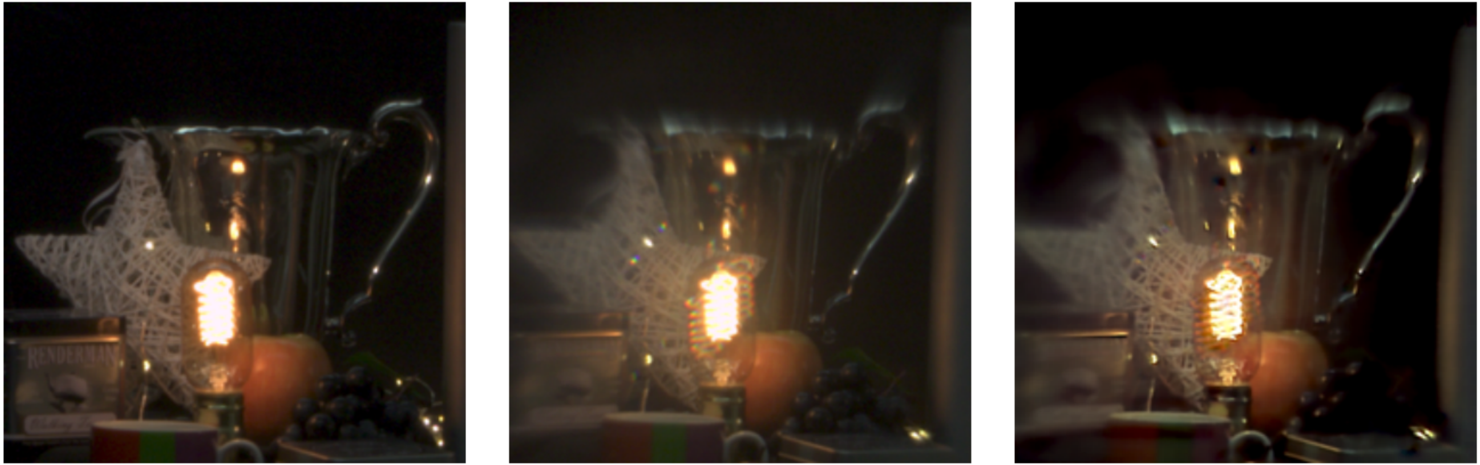
[Metzler '20]

Deep optics for HDR imaging



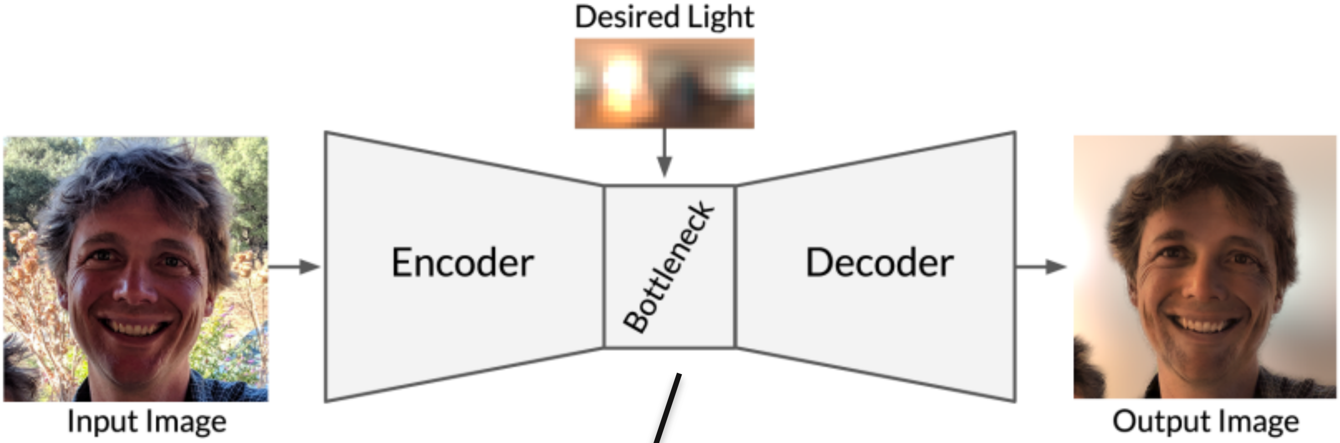
[Metzler '20]

LDR Image | E2E Measurement | E2E Reconstruction



[Metzler '20]

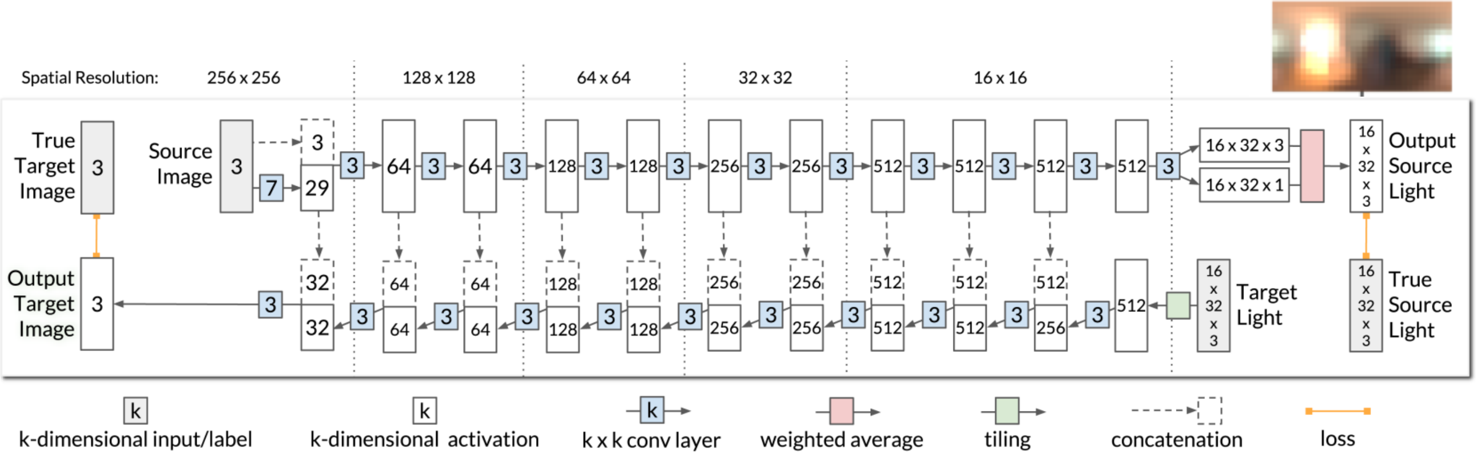
Image Relighting



U-Net

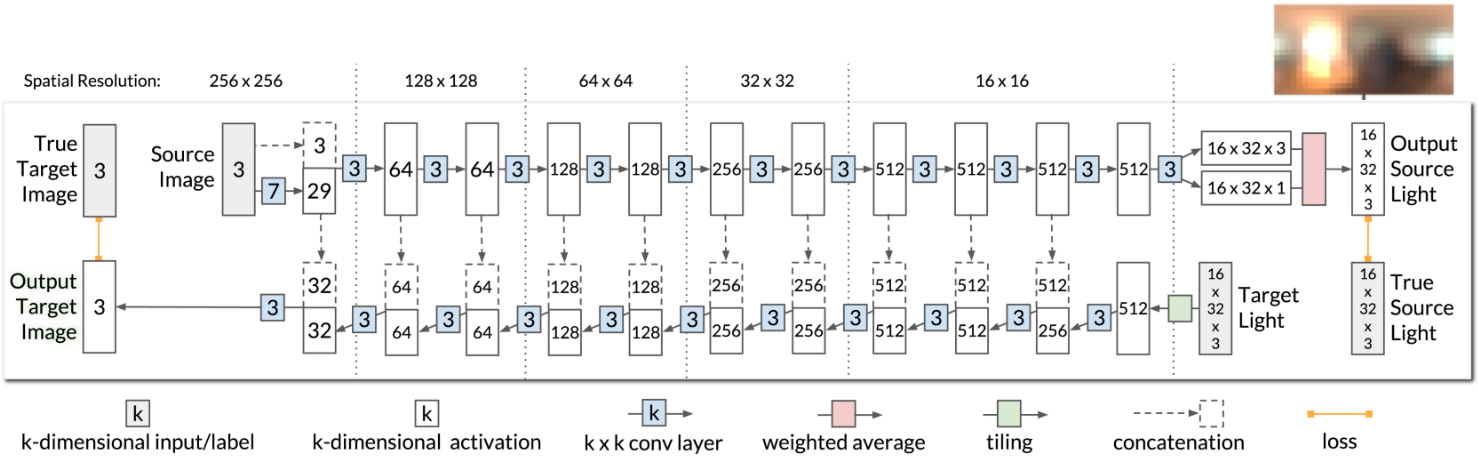
[Sun '19]

Image Relighting



[Sun '19]

Image Relighting



How would you train this network?

[Sun '19]

Image Relighting

Light-stage dataset capture (Google)

[Sun ‘19]

Image Relighting

OLAT photos
(columns)

$$b = Ax$$

Re-rendered
image

Environment
map

(a) OLAT images (7 cameras).

(b) Ground-truth renderings.

[Sun '19]

Image Relighting

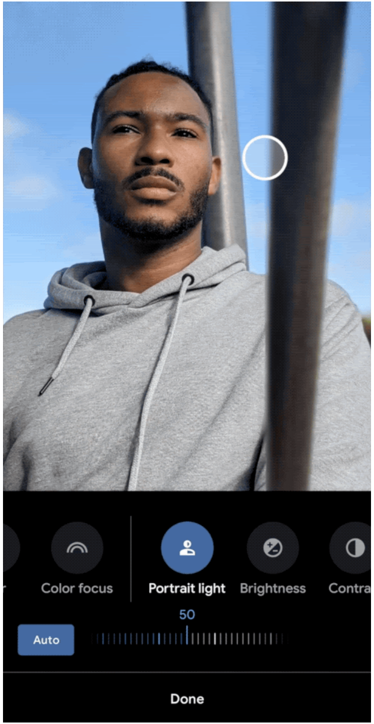
(a) Input image and estimated lighting

(b) Rendered images from our method under three novel illuminations

[Sun ‘19]

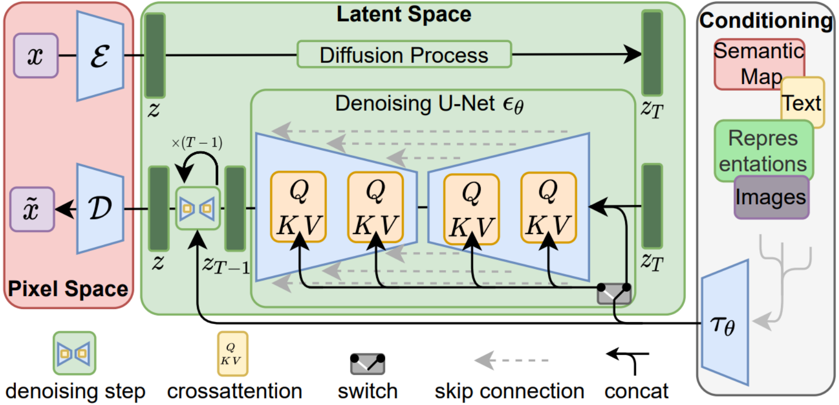
Image Relighting

Now a feature in pixel phones



[Sun '19]

Image Generation



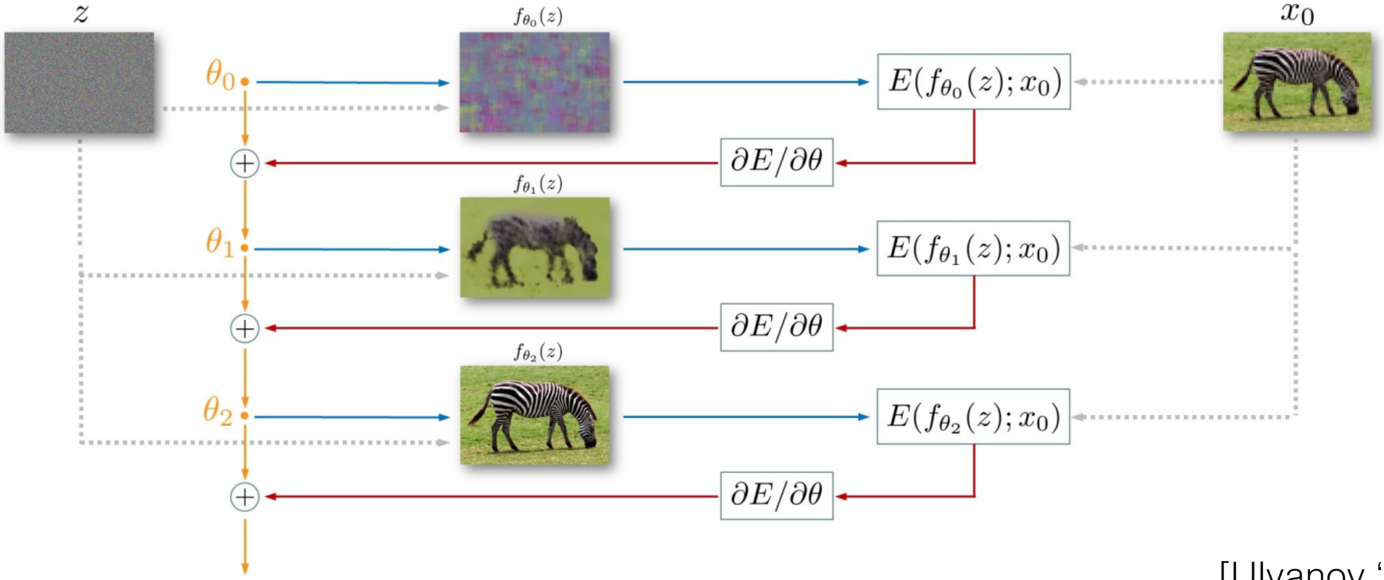
Text-to-Image Synthesis on LAION. 1.45B Model.

'A street sign that reads "Latent Diffusion" '	'A zombie in the style of Picasso'	'An image of an animal half mouse half octopus'	'An illustration of a slightly conscious neural network'	'A painting of a squirrel eating a burger'	'A watercolor painting of a chair that looks like an octopus'	'A shirt with the inscription: "I love generative models!" '

Do we always need training datasets?

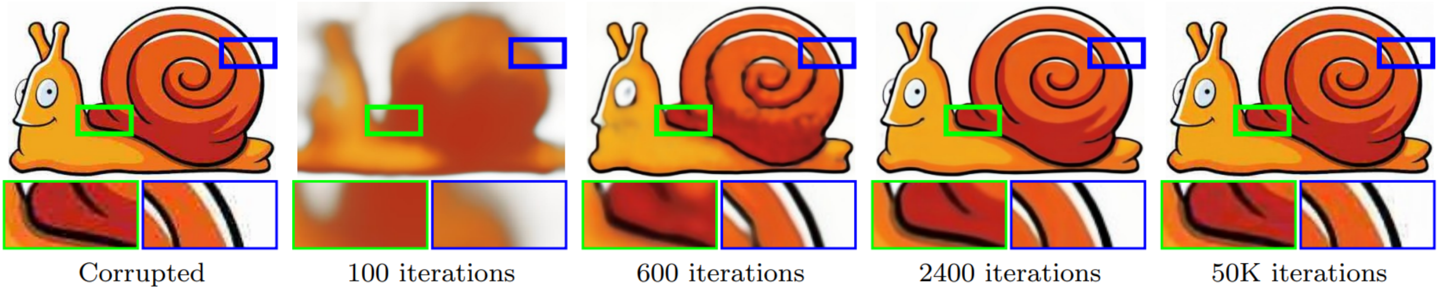
Deep image prior

Idea: Overfit a U-Net to a noisy image, but stop training early



[Ulyanov '20]

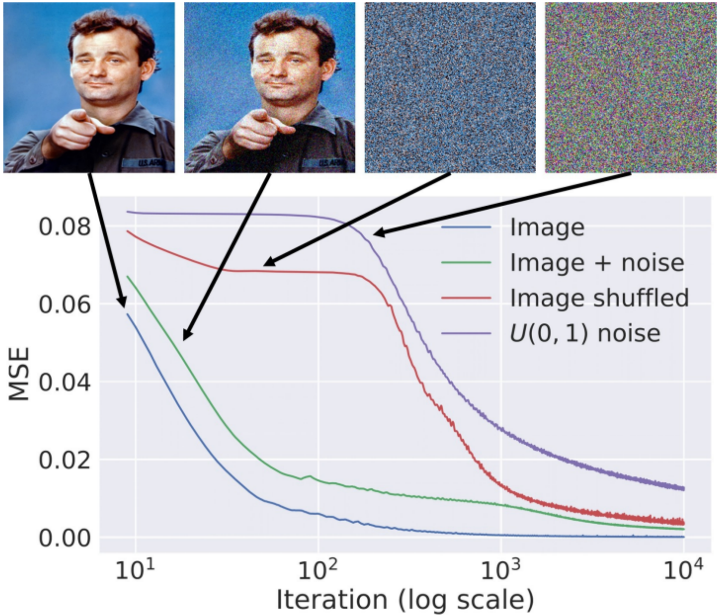
Deep image prior



The CNN itself is a good prior for natural images

[Ulyanov '20]

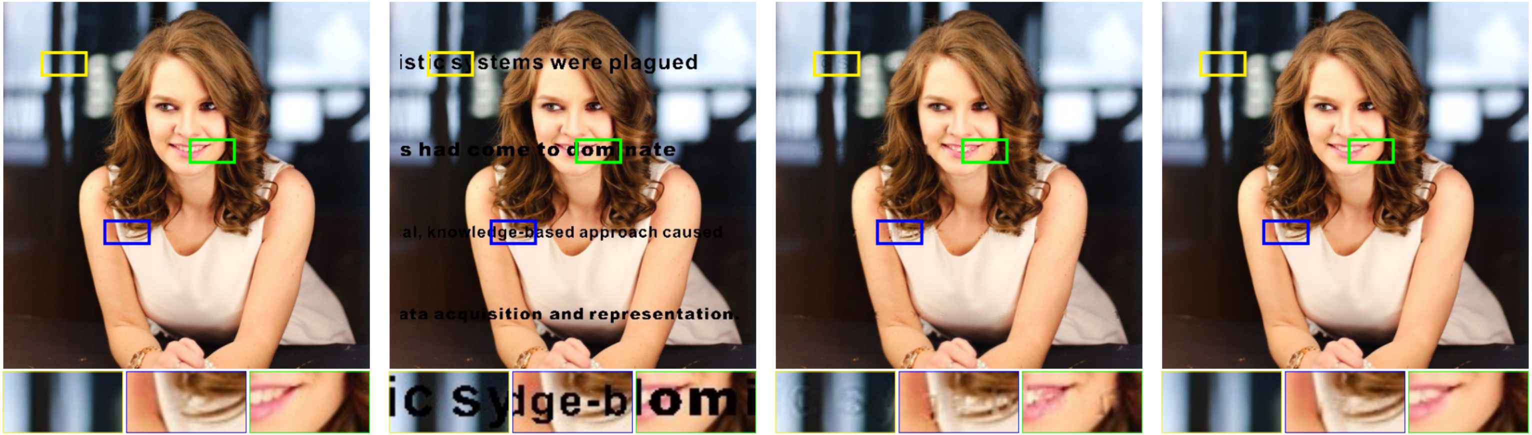
Deep image prior



During training, the network fits the image before noise

[Ulyanov '20]

Deep image prior



GT   Corrupted   Trained CNN   DIP

[Ulyanov ‘20]

Summary

- “Neural” Networks & CNNs
- Building blocks of CNNs and deep networks
- Applications & inverse problems
- Just scratches the surface!
    - GANs, diffusion models, neural fields, neural rendering, text-to-image models, autoregressive models, transformers…

Next Time

- Optimization using alternating direction method of multipliers
- Hybrid techniques!

References and Further Reading

slides adapted from Stanford CS231N: http://cs231n.stanford.edu/slides/

CS229/CS231n notes on linear classifiers

https://cs231n.github.io/linear-classify/

https://cs229.stanford.edu/notes2021fall/cs229-notes1.pdf

CS231n Notes on backprop

http://cs231n.stanford.edu/handouts/linear-backprop.pdf

https://cs231n.github.io/optimization-2/

Intro to pytorch autograd

https://pytorch.org/tutorials/beginner/blitz/autograd_tutorial.html

Extending pytorch autograd functions

https://pytorch.org/docs/stable/notes/extending.html

References and Further Reading

slides adapted from Stanford CS231N: http://cs231n.stanford.edu/slides/

Araujo, André, Wade Norris, and Jack Sim. "Computing receptive fields of convolutional neural networks." *Distill* 4.11 (2019)

Chen, Chen, et al. "Learning to see in the dark." *Proc. CVPR*. 2018.

Eigen, David, Christian Puhrsch, and Rob Fergus. "Depth map prediction from a single image using a multi-scale deep network." *Proc. NeurIPS.* (2014).

Farabet, Clement, et al. "Learning hierarchical features for scene labeling." *IEEE TPAMI.* 35.8 (2012): 1915-1929.

He, Kaiming, et al. "Deep residual learning for image recognition." Proc. CVPR. 2016.

Hubel, David H., and Torsten N. Wiesel. "Receptive fields of single neurones in the cat's striate cortex." *The Journal of physiology* 148.3 (1959): 574-591.

Krizhevsky, Alex, Ilya Sutskever, and Geoffrey E. Hinton. "Imagenet classification with deep convolutional neural networks." *Proc. NeurIPS* 25 (2012): 1097-1105.

Lim, Bee, et al. "Enhanced deep residual networks for single image super-resolution." *Proc. CVPR Workshops*. 2017.

Lin, Haoning, Zhenwei Shi, and Zhengxia Zou. "Maritime semantic labeling of optical remote sensing images with multi-scale fully convolutional network." *Remote sens.* 9.5 (2017): 480.

Metzler, Christopher A., et al. "Deep optics for single-shot high-dynamic-range imaging." Proc. CVPR. 2020.

Nah, Seungjun, Tae Hyun Kim, and Kyoung Mu Lee. "Deep multi-scale convolutional neural network for dynamic scene deblurring." *Proc. CVPR*. 2017.

Odena, Augustus, Vincent Dumoulin, and Chris Olah. "Deconvolution and checkerboard artifacts." *Distill* 1.10 (2016)

Olah, Chris, Alexander Mordvintsev, and Ludwig Schubert. "Feature visualization." *Distill* 2.11 (2017)

Ronneberger, Olaf, Philipp Fischer, and Thomas Brox. "U-net: Convolutional networks for biomedical image segmentation." *International Conference on Medical image computing and computer-assisted intervention*. 2015.

Ren, Shaoqing, et al. "Faster R-CNN: towards real-time object detection with region proposal networks." *IEEE TPAMI.* 39.6 (2016): 1137-1149.

Russakovsky, Olga, et al. "Imagenet large scale visual recognition challenge." *IJCV* 115.3 (2015): 211-252.

Simonyan, Karen, and Andrew Zisserman. "Very deep convolutional networks for large-scale image recognition." *Proc. ICLR* (2014).

Sun, Tiancheng, et al. "Single image portrait relighting." *ACM Trans. Graph.* 38.4 (2019): 79-1.

Toshev, Alexander, and Christian Szegedy. "Deeppose: Human pose estimation via deep neural networks." *Proc. CVPR*. 2014.

Ulyanov, Dmitry, Andrea Vedaldi, and Victor Lempitsky. "Deep image prior." *Proc. CVPR.* 2018.

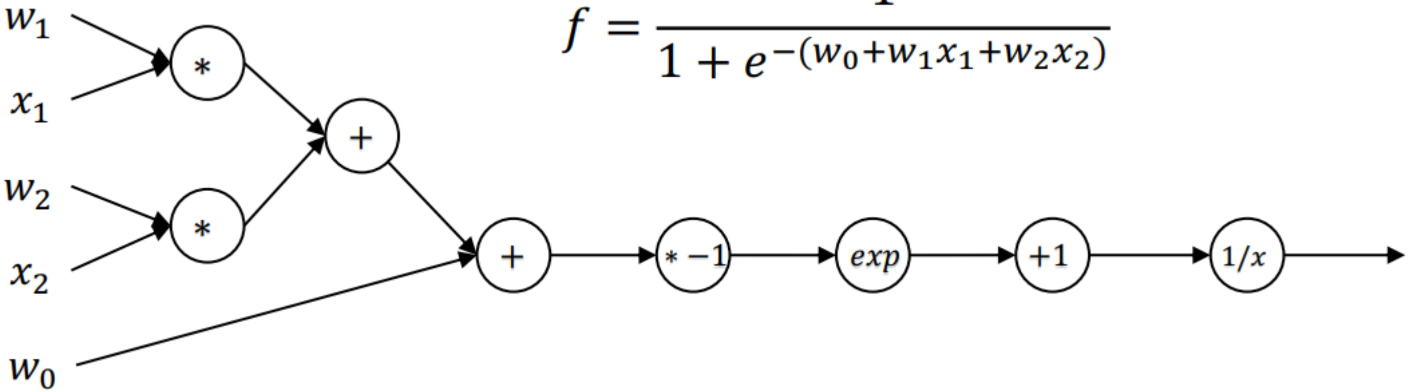
Zhang, Kai, et al. "Beyond a gaussian denoiser: Residual learning of deep cnn for image denoising." *IEEE Trans. Imag. Proc.* 26.7 (2017): 3142-3155.

Extra backpropagation example (from Stanford CS231n)

$$f = \frac{1}{1 + e^{-(w_0 + w_1 x_1 + w_2 x_2)}}$$

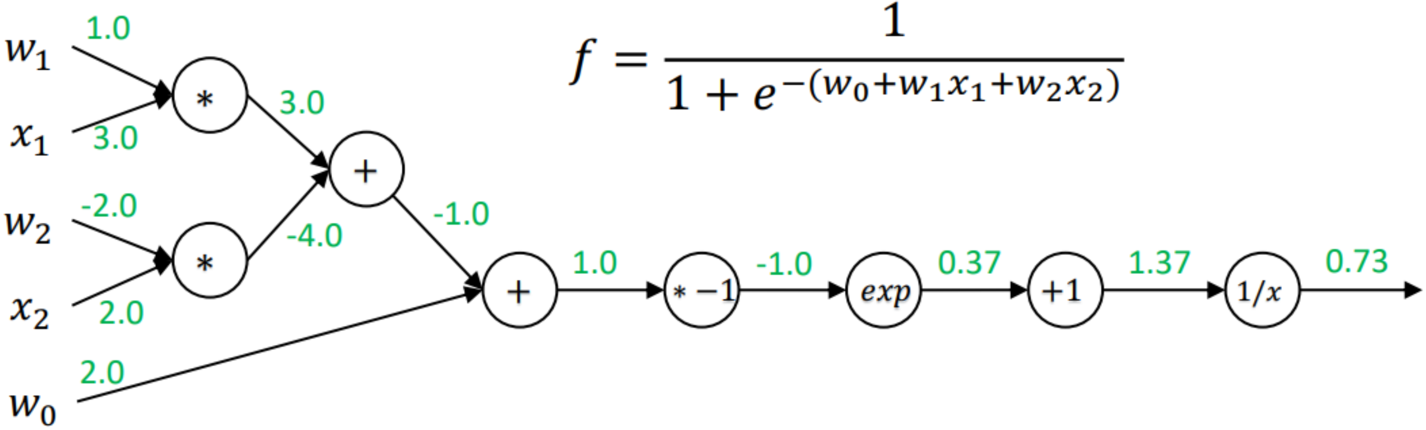
Extra backpropagation example

$$f = \frac{1}{1 + e^{-(w_0 + w_1 x_1 + w_2 x_2)}}$$



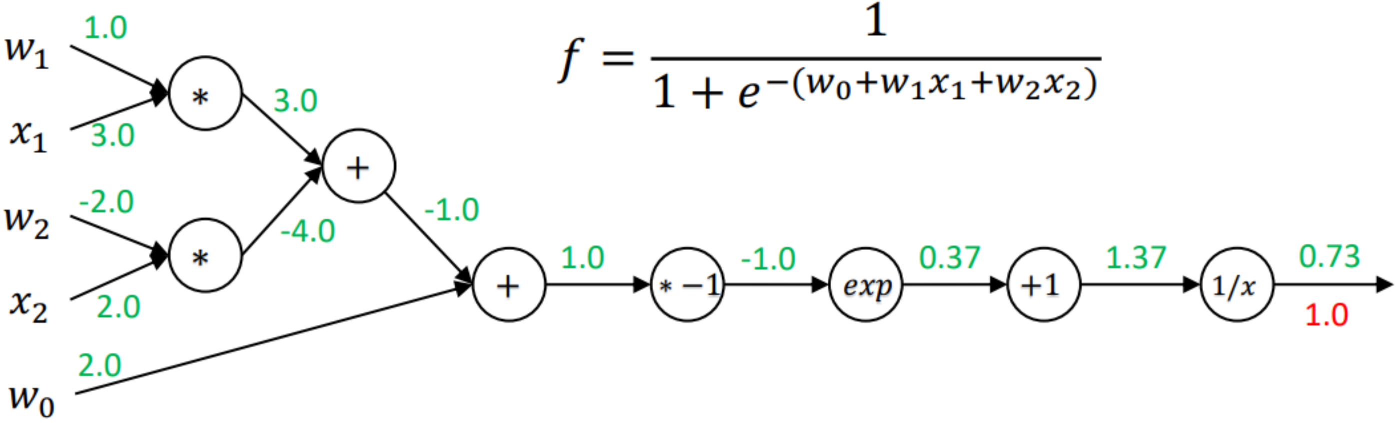
Extra backpropagation example

$$f = \frac{1}{1 + e^{-(w_0 + w_1 x_1 + w_2 x_2)}}$$

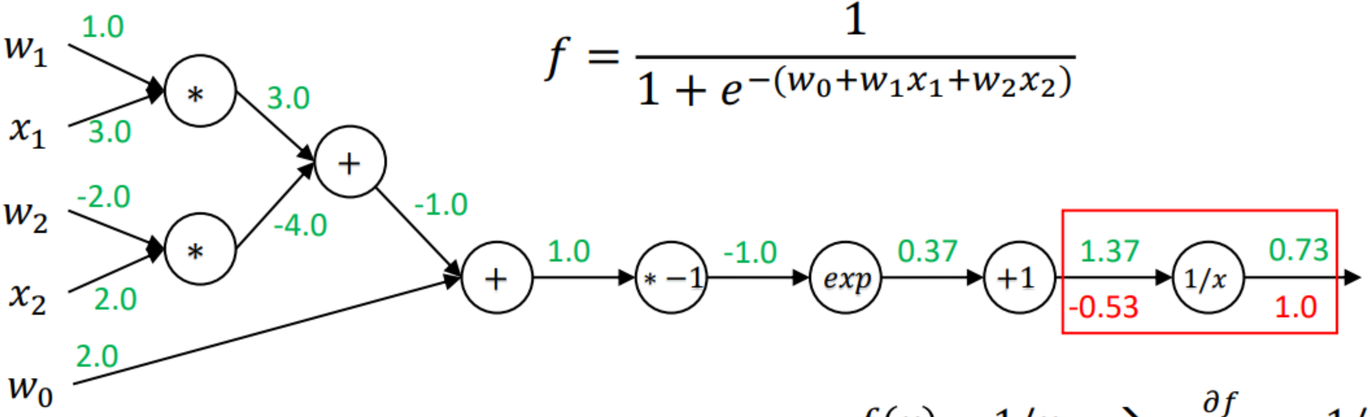


Extra backpropagation example

$$f = \frac{1}{1 + e^{-(w_0 + w_1 x_1 + w_2 x_2)}}$$



Extra backpropagation example



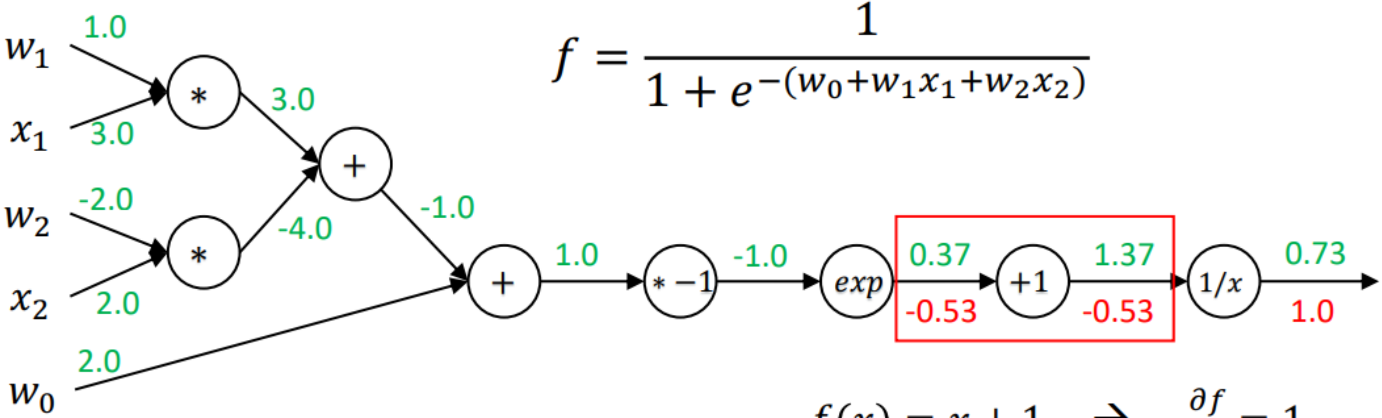
$$f = \frac{1}{1 + e^{-(w_0 + w_1 x_1 + w_2 x_2)}}$$

$$f(x) = 1/x \quad \rightarrow \quad \frac{\partial f}{\partial x} = -1/x^2$$

$$\frac{\partial J}{\partial x} = \frac{\partial J}{\partial f}\frac{\partial f}{\partial x} = -1/x^2$$

Extra backpropagation example

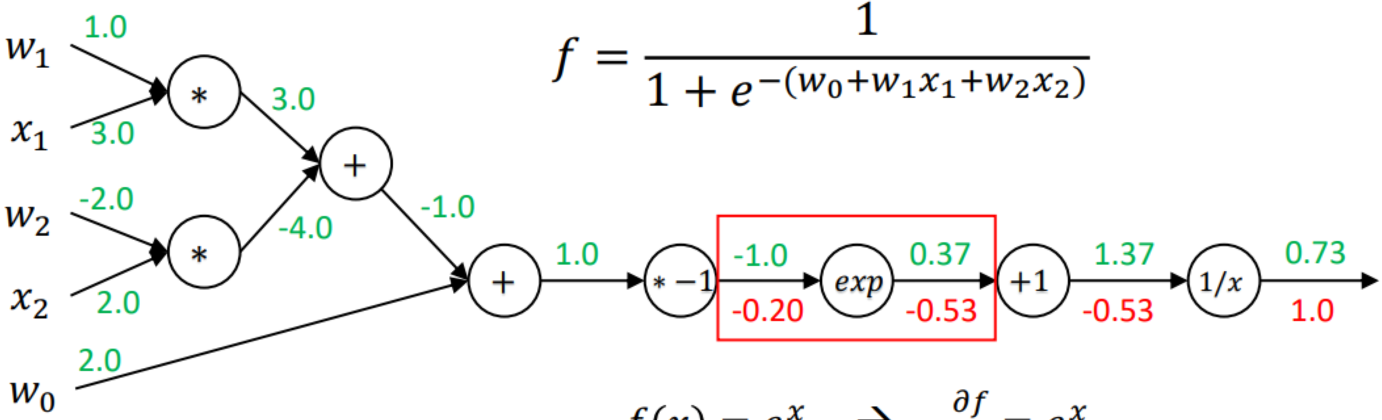
$$f = \frac{1}{1 + e^{-(w_0 + w_1 x_1 + w_2 x_2)}}$$



$$f(x) = x + 1 \quad \rightarrow \quad \frac{\partial f}{\partial x} = 1$$

Extra backpropagation example

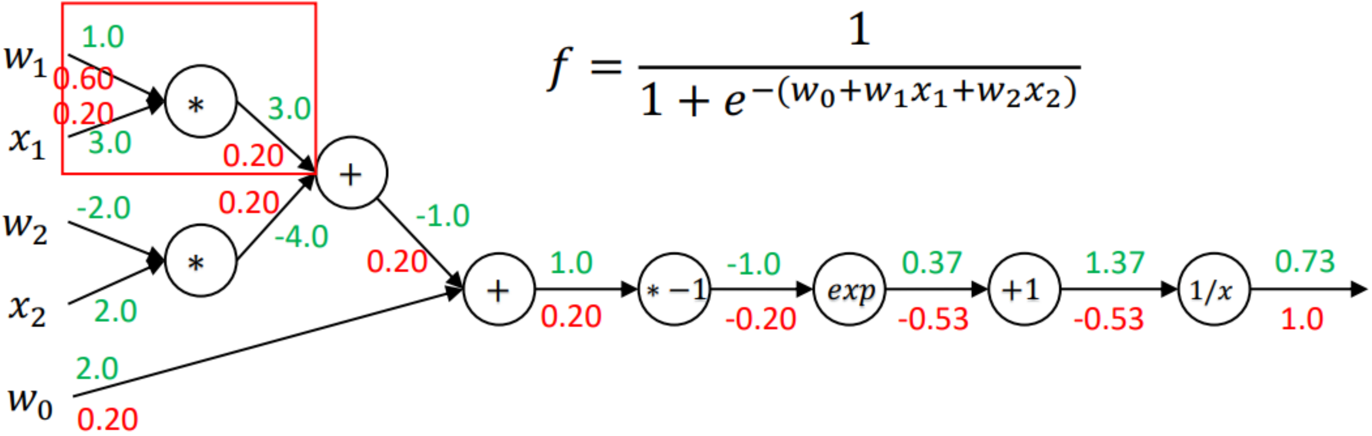
$$f = \frac{1}{1 + e^{-(w_0 + w_1 x_1 + w_2 x_2)}}$$



$$f(x) = e^x \quad \rightarrow \quad \frac{\partial f}{\partial x} = e^x$$

$$\frac{\partial J}{\partial x} = \frac{\partial J}{\partial f}\frac{\partial f}{\partial x} = \frac{\partial J}{\partial f} \cdot e^x$$

Extra backpropagation example



$$f = \frac{1}{1 + e^{-(w_0 + w_1 x_1 + w_2 x_2)}}$$

$$f(x, w) = xw \quad \rightarrow \quad \frac{\partial f}{\partial x} = w, \ \frac{\partial f}{\partial w} = x$$

Extra backpropagation example

$$f = \frac{1}{1 + e^{-(w_0 + w_1 x_1 + w_2 x_2)}}$$