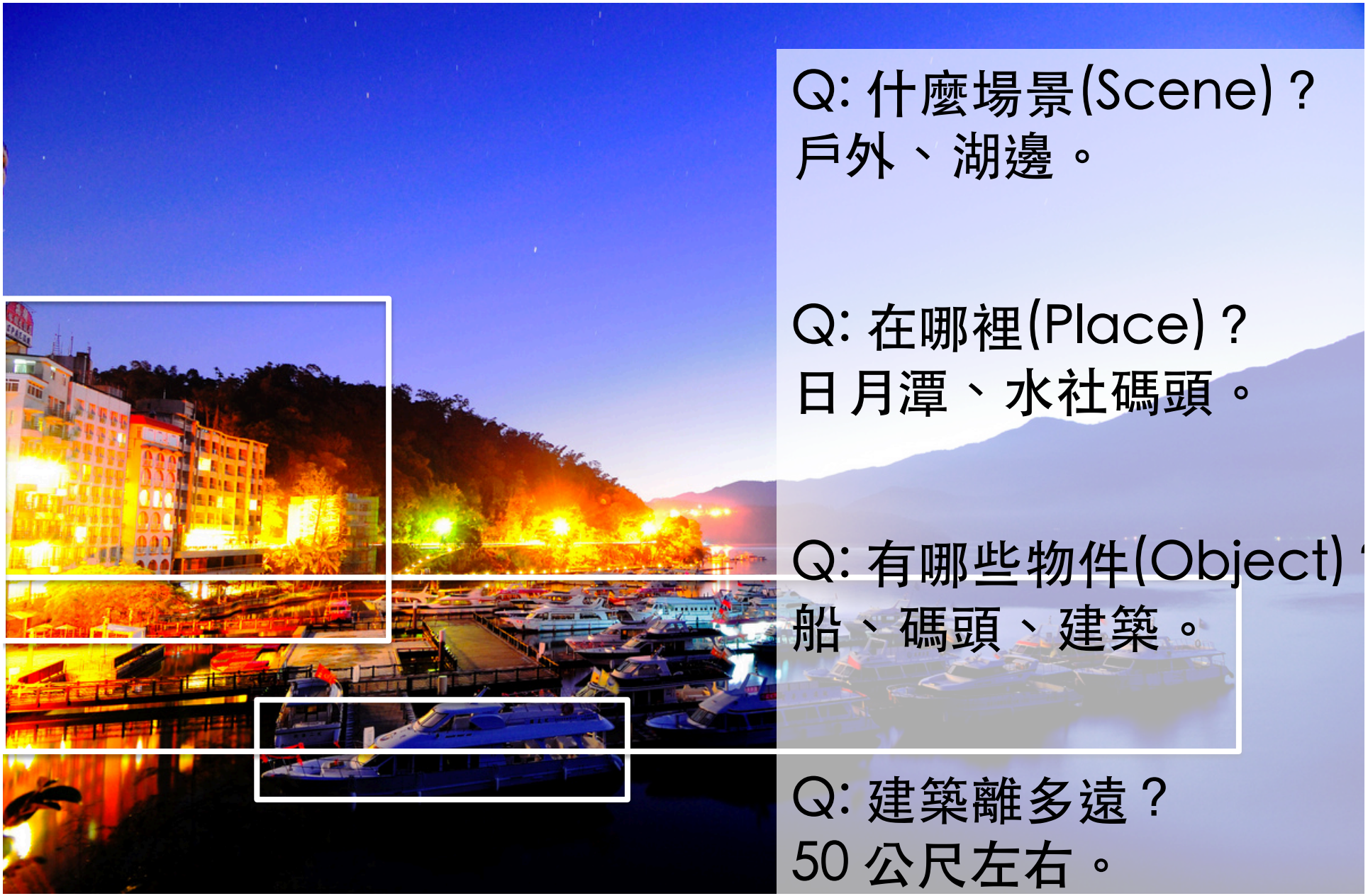
# Deep Learning in Computer Vision – Convolutional Neural Network

國立清華大學

孫民教授


VSLab

# 電腦視覺 Computer Vision



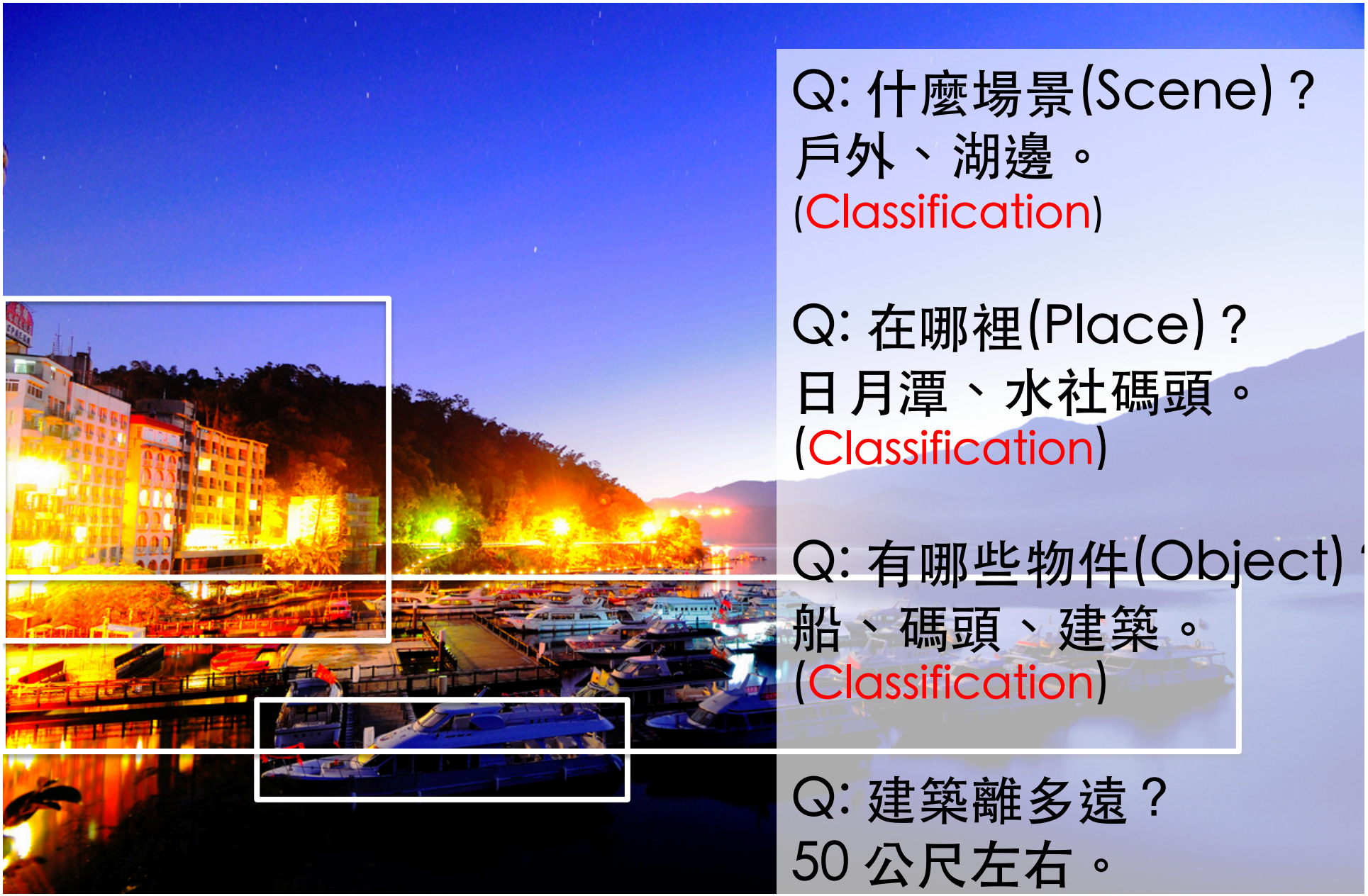
Q: 什麼場景(Scene)？
戶外、湖邊。

Q: 在哪裡(Place)？
日月潭、水社碼頭。

Q: 有哪些物件(Object)？
船、碼頭、建築。

Q: 建築離多遠？
50 公尺左右。

# 電腦視覺 Computer Vision



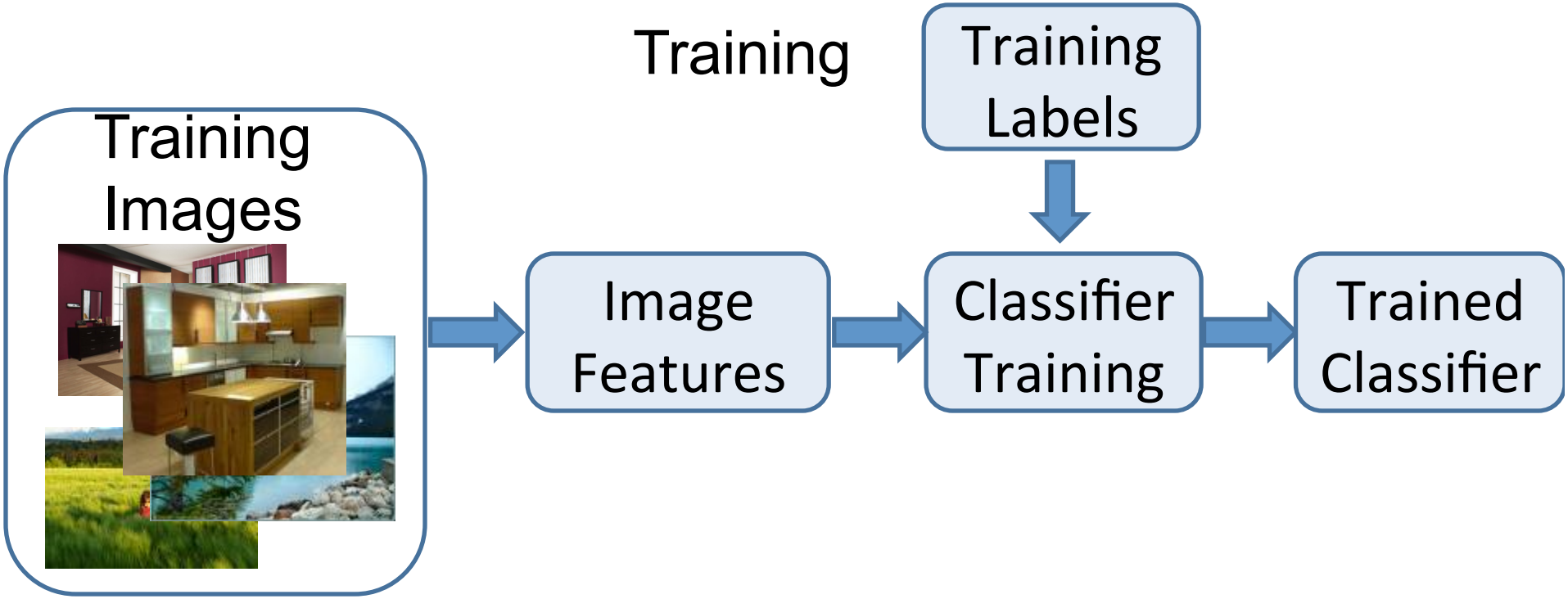
Q: 什麼場景(Scene)？
戶外、湖邊。
(Classification)

Q: 在哪裡(Place)？
日月潭、水社碼頭。
(Classification)

Q: 有哪些物件(Object)？
船、碼頭、建築。
(Classification)

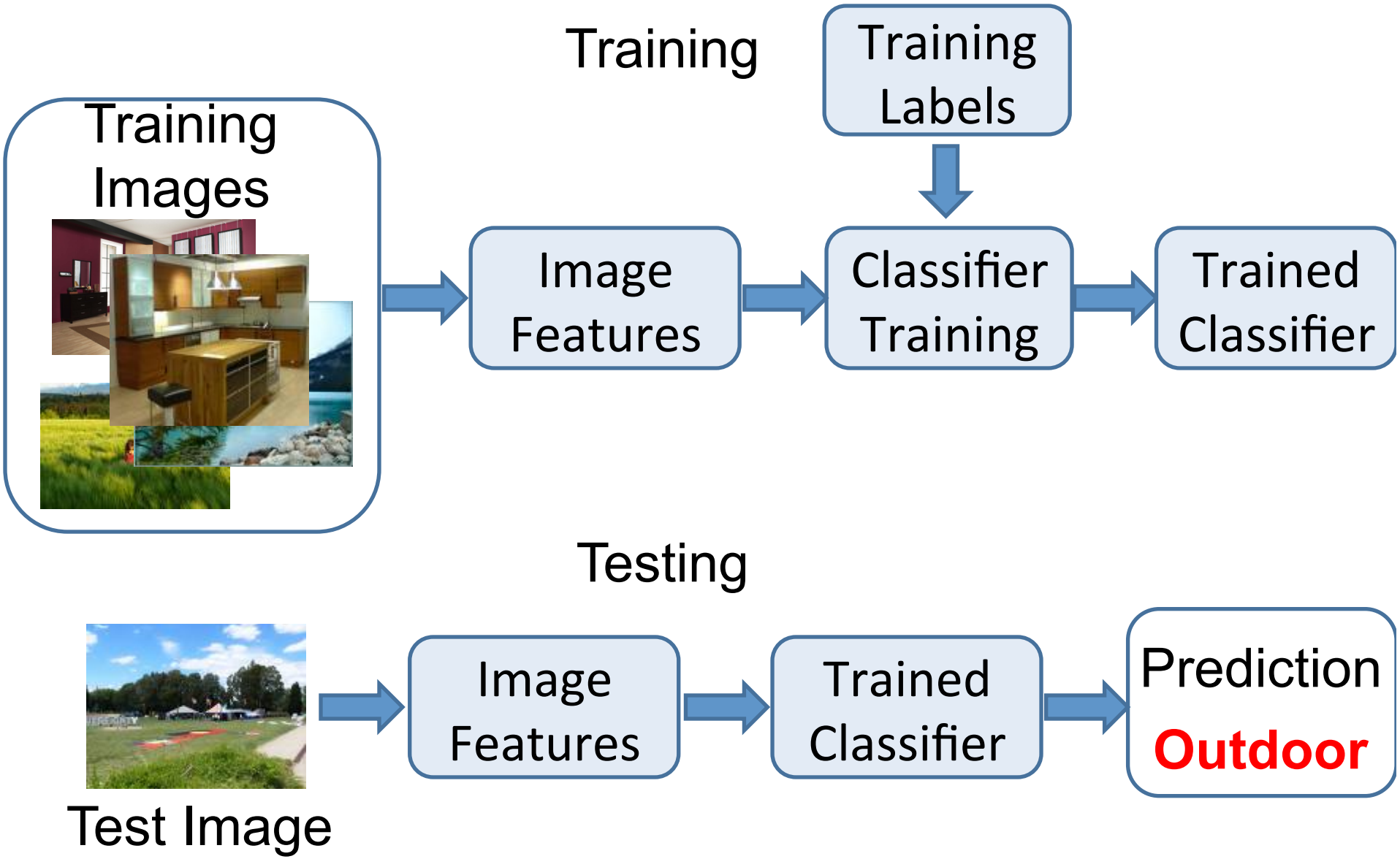
Q: 建築離多遠？
50 公尺左右。

# Image Classification

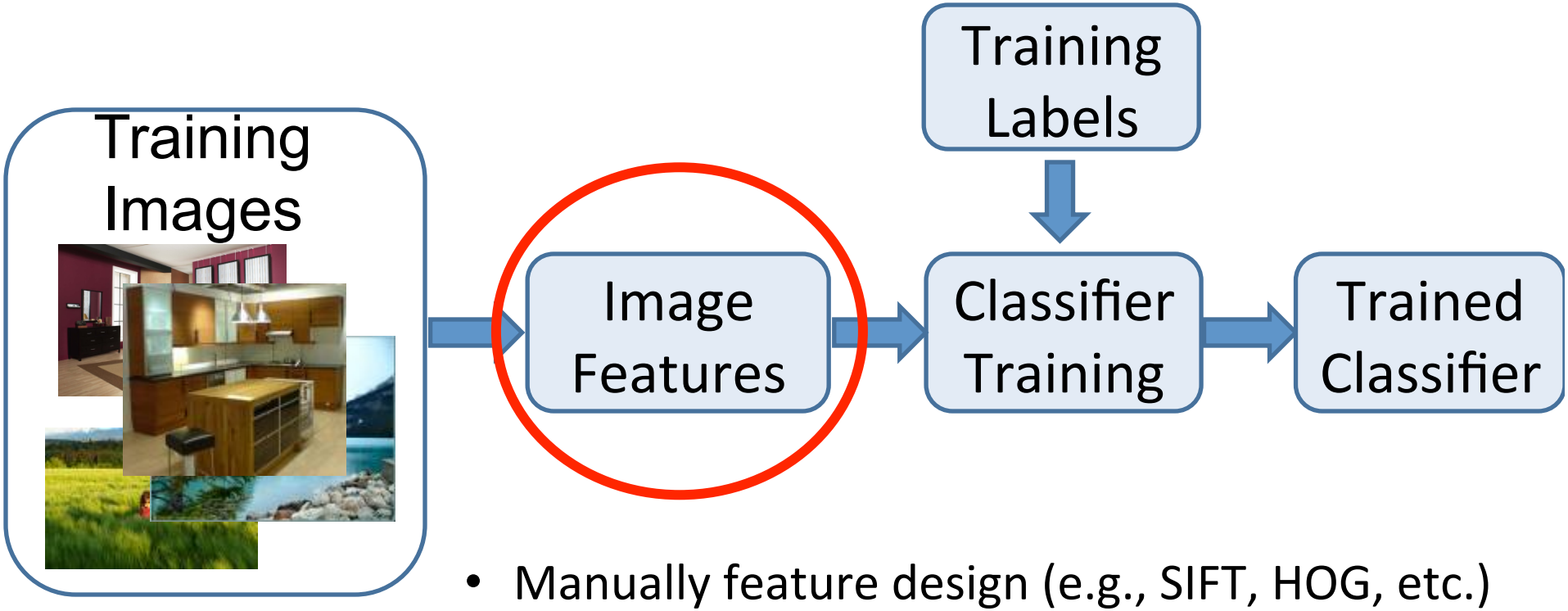



Slides: Jame Hays, Isabelle Guyon, Erik Sudderth, Mark Johnson, Derek Hoiem

# Image Classification



# Image Classification

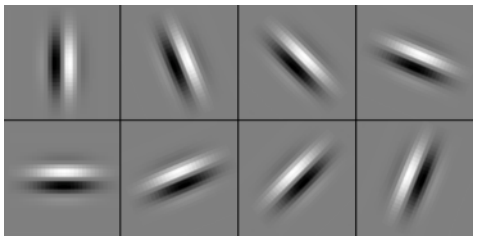



- Manually feature design (e.g., SIFT, HOG, etc.)
- Multiple separately learned layers
  (e.g., K-means, Pyramid, etc.)

# SIFT Descriptor

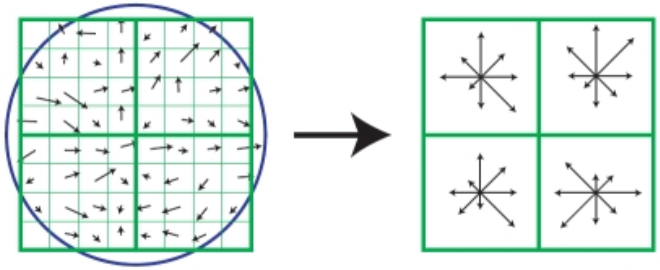
Image Pixels

Apply oriented filters

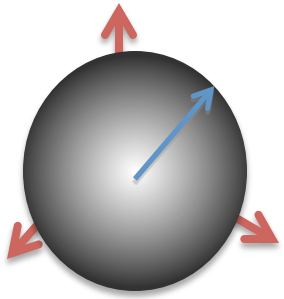


Lowe [IJCV 2004]

Spatial pool (Sum)



Normalize to unit length



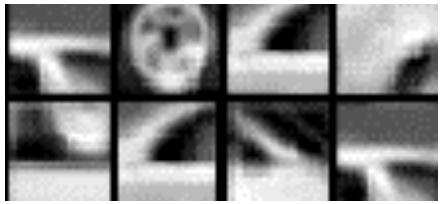
Feature Vector

slide credit: R. Fergus

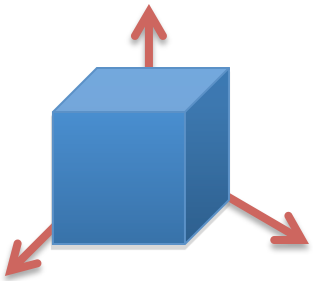
# Spatial Pyramid Matching

SIFT Features

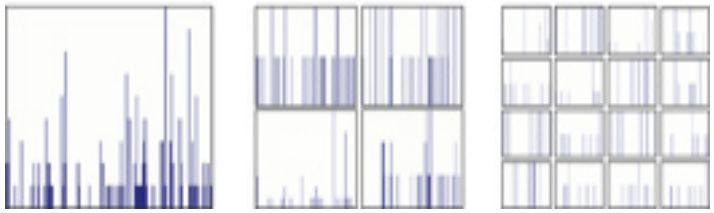
Filter with Visual Words



Max



Multi-scale spatial pool (Sum)



Classifier

Lazebnik, Schmid, Ponce [CVPR 2006]

slide credit: R. Fergus

# Comparison

- Classical CV

Hand-crafted Feature Extractor → "Simple" Trainable Classifier

- Deep Learning

**Trainable** Feature Extractor → **Trainable** Classifier

**End-to-End Learning**

Slides: Y LeCun
MA Ranzato

SIFT HoG

K-means Sparse Coding

Pooling

Classifier

Fixed

Unsupervised

supervised

Low-level Features

Mid-level Features

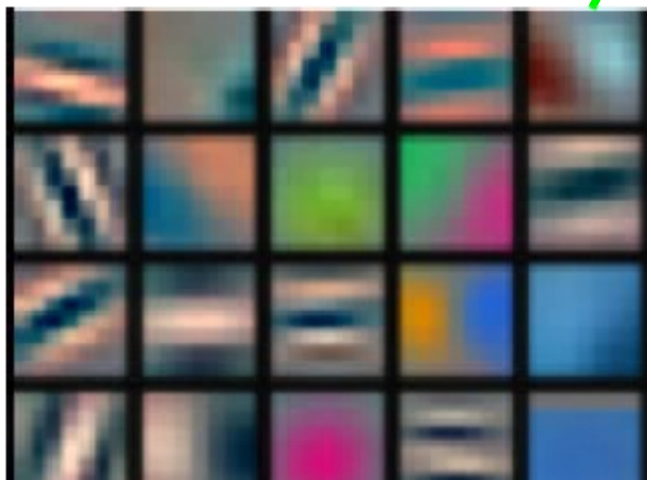
2012

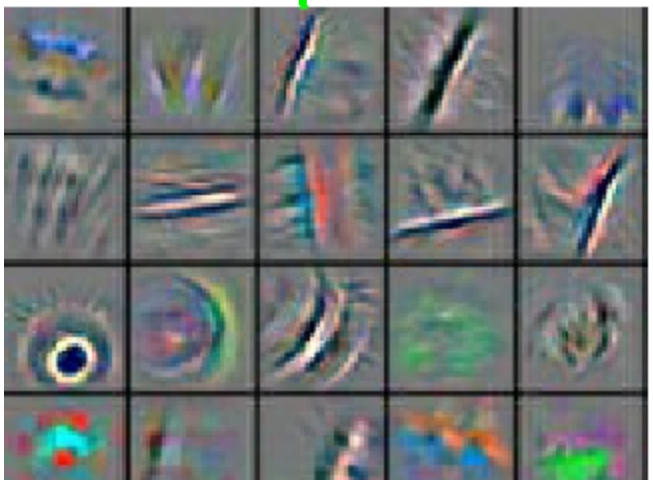
Low-Level Feature

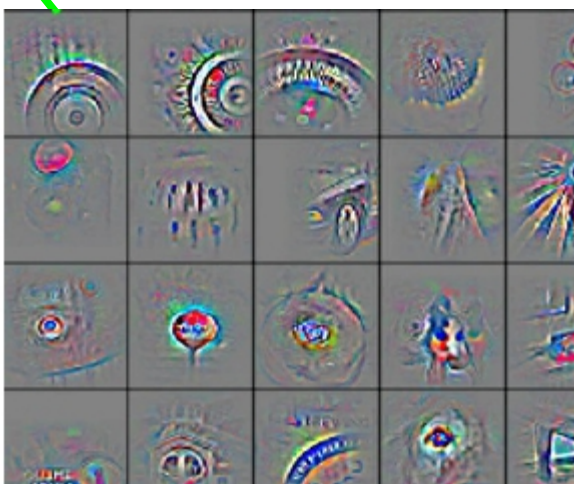
Mid-Level Feature

High-Level Feature

Trainable Classifier







# 1K Image Classification

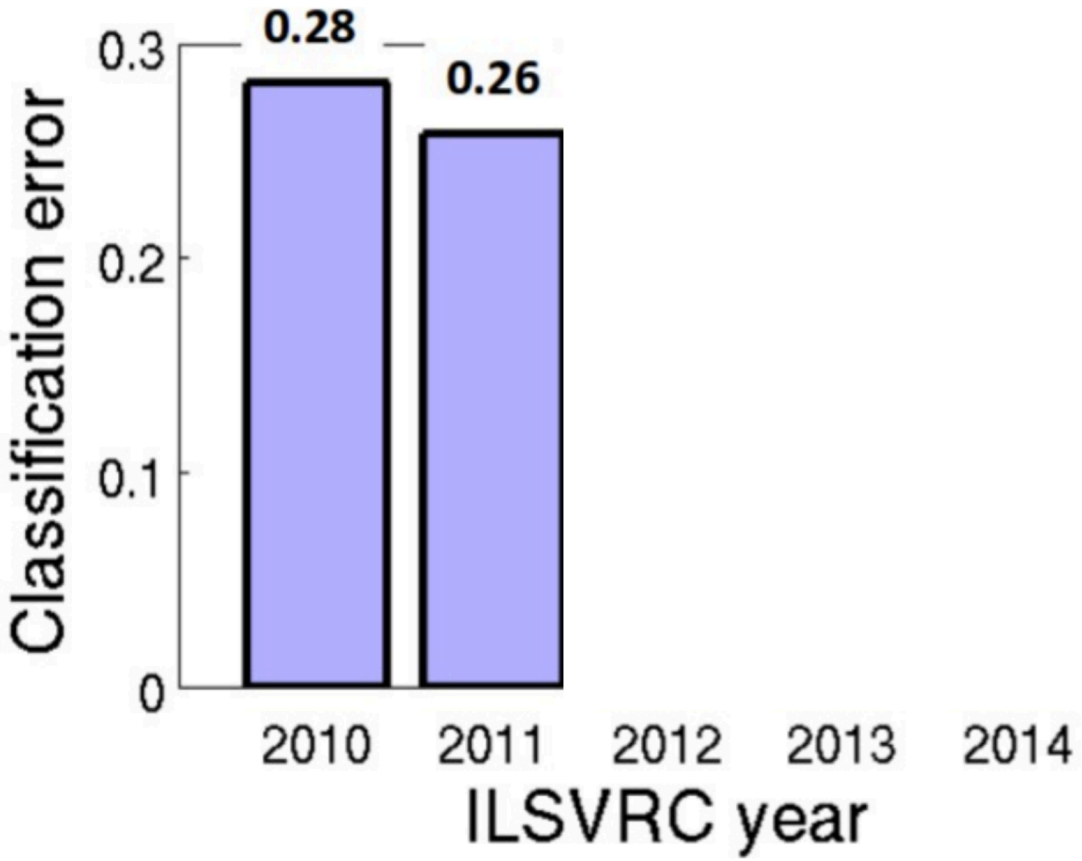



Figure from Olga Russakovsky ECCV'14 workshop

Deep Learning

# 1K Image Classification

## Convolution Neuron Networks (CNN)

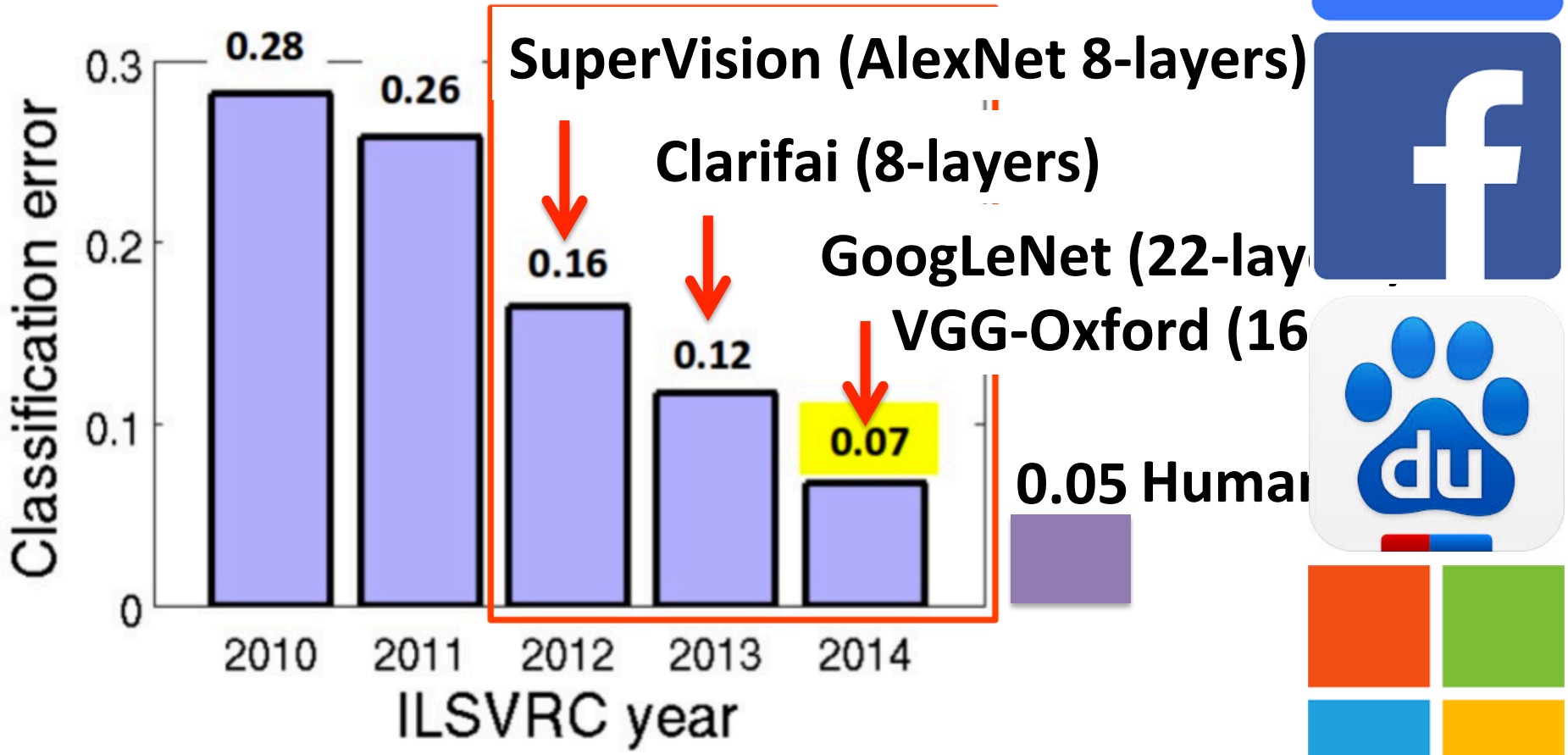
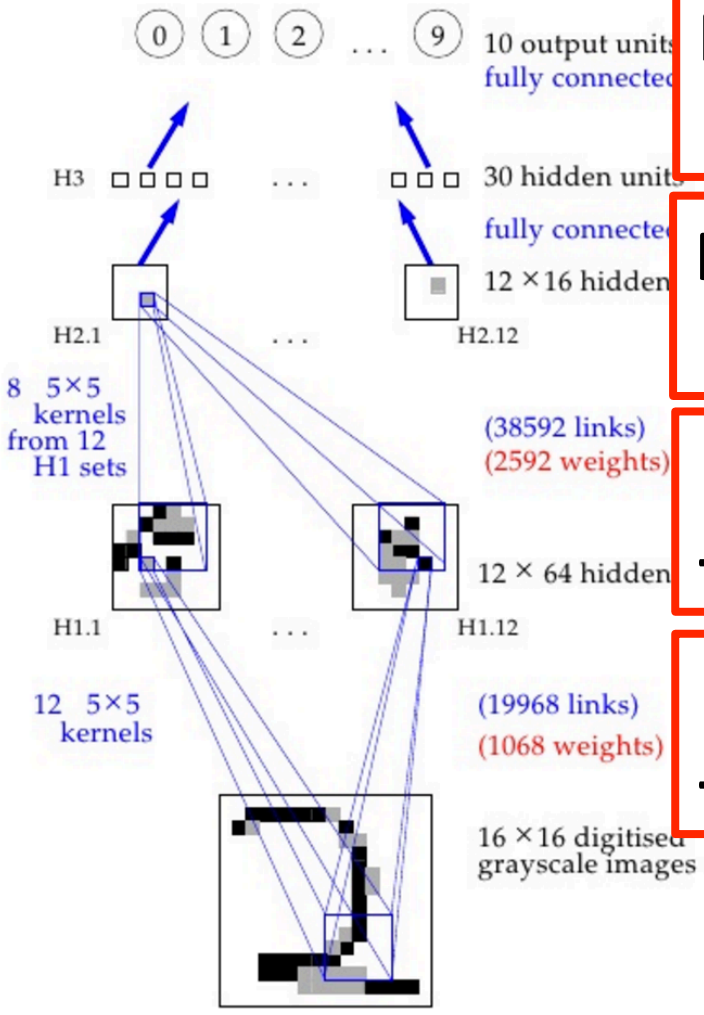



Figure from Olga Russakovsky ECCV'14 workshop

# Classic CNN: LeNet



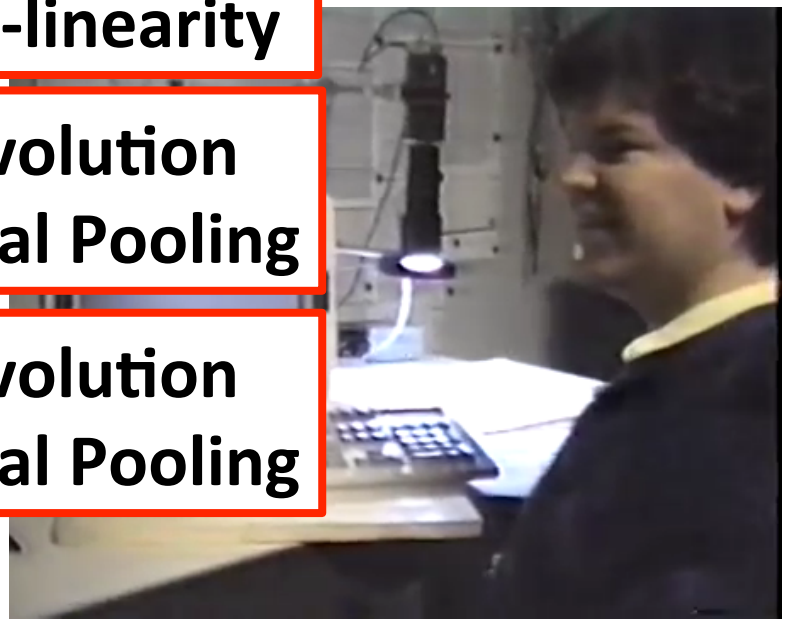

Before weight sharing 64660 links
After weight sharing 9760 weights

**Fully Connected + Non-linearity**

**Fully Connected + Non-linearity**

**Convolution +Spatial Pooling**

**Convolution +Spatial Pooling**



**LeNet-1, 1993**

**Backpropagation Applied to Handwritten Zip Code. Yann Lecun, 1989**

# What is 2D Convolution?

## Image filtering

$g[\cdot,\cdot]$ $\frac{1}{9}$

| | | |
|---|---|---|
| 1 | 1 | 1 |
| 1 | 1 | 1 |
| 1 | 1 | 1 |

$f[.,.]$

| | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 0 | 0 | 0 | 90 | 90 | 90 | 90 | 90 | 0 | 0 |
| 0 | 0 | 0 | 90 | 90 | 90 | 90 | 90 | 0 | 0 |
| 0 | 0 | 0 | 90 | 90 | 90 | 90 | 90 | 0 | 0 |
| 0 | 0 | 0 | 90 | 0 | 90 | 90 | 90 | 0 | 0 |
| 0 | 0 | 0 | 90 | 90 | 90 | 90 | 90 | 0 | 0 |
| 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 0 | 0 | 90 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |

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$$h[m,n] = \sum_{k,l} g[k,l]\, f[m+k,n+l]$$



Credit: S. Seitz

# Image filtering

$g[\cdot,\cdot]$ $\frac{1}{9}$

| | | |
|---|---|---|
| 1 | 1 | 1 |
| 1 | 1 | 1 |
| 1 | 1 | 1 |

$f[.,.]$

| | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 0 | 0 | 0 | 90 | 90 | 90 | 90 | 90 | 0 | 0 |
| 0 | 0 | 0 | 90 | 90 | 90 | 90 | 90 | 0 | 0 |
| 0 | 0 | 0 | 90 | 90 | 90 | 90 | 90 | 0 | 0 |
| 0 | 0 | 0 | 90 | 0 | 90 | 90 | 90 | 0 | 0 |
| 0 | 0 | 0 | 90 | 90 | 90 | 90 | 90 | 0 | 0 |
| 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 0 | 0 | 90 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |

$h[.,.]$

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$$h[m,n] = \sum_{k,l} g[k,l]\, f[m+k,n+l]$$



Credit: S. Seitz

# Image filtering

$g[\cdot,\cdot]$ $\frac{1}{9}$

| | | |
|---|---|---|
| 1 | 1 | 1 |
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| 1 | 1 | 1 |

$f[.,.]$

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| 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 0 | 0 | 0 | 90 | 90 | 90 | 90 | 90 | 0 | 0 |
| 0 | 0 | 0 | 90 | 90 | 90 | 90 | 90 | 0 | 0 |
| 0 | 0 | 0 | 90 | 90 | 90 | 90 | 90 | 0 | 0 |
| 0 | 0 | 0 | 90 | 0 | 90 | 90 | 90 | 0 | 0 |
| 0 | 0 | 0 | 90 | 90 | 90 | 90 | 90 | 0 | 0 |
| 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 0 | 0 | 90 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |

$h[.,.]$

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$$h[m,n] = \sum_{k,l} g[k,l]\, f[m+k,n+l]$$



Credit: S. Seitz

# Image filtering

$g[\cdot,\cdot]$ $\frac{1}{9}$

| | | |
|---|---|---|
| 1 | 1 | 1 |
| 1 | 1 | 1 |
| 1 | 1 | 1 |

$f[.,.]$

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|---|---|---|---|---|---|---|---|---|---|
| 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 0 | 0 | 0 | 90 | 90 | 90 | 90 | 90 | 0 | 0 |
| 0 | 0 | 0 | 90 | 90 | 90 | 90 | 90 | 0 | 0 |
| 0 | 0 | 0 | 90 | 90 | 90 | 90 | 90 | 0 | 0 |
| 0 | 0 | 0 | 90 | 0 | 90 | 90 | 90 | 0 | 0 |
| 0 | 0 | 0 | 90 | 90 | 90 | 90 | 90 | 0 | 0 |
| 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 0 | 0 | 90 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |

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$$h[m,n] = \sum_{k,l} g[k,l]\, f[m+k,n+l]$$



Credit: S. Seitz

# Image filtering

$g[\cdot,\cdot]$ $\frac{1}{9}$

| | | |
|---|---|---|
| 1 | 1 | 1 |
| 1 | 1 | 1 |
| 1 | 1 | 1 |

$f[.,.]$

| | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 0 | 0 | 0 | 90 | 90 | 90 | 90 | 90 | 0 | 0 |
| 0 | 0 | 0 | 90 | 90 | 90 | 90 | 90 | 0 | 0 |
| 0 | 0 | 0 | 90 | 90 | 90 | 90 | 90 | 0 | 0 |
| 0 | 0 | 0 | 90 | 0 | 90 | 90 | 90 | 0 | 0 |
| 0 | 0 | 0 | 90 | 90 | 90 | 90 | 90 | 0 | 0 |
| 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 0 | 0 | 90 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |

$h[.,.]$

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$$h[m,n] = \sum_{k,l} g[k,l]\, f[m+k,n+l]$$



Credit: S. Seitz

# Image filtering

$g[\cdot,\cdot]$ $\frac{1}{9}$

| | | |
|---|---|---|
| 1 | 1 | 1 |
| 1 | 1 | 1 |
| 1 | 1 | 1 |

$f[.,.]$

| | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 0 | 0 | 0 | 90 | 90 | 90 | 90 | 90 | 0 | 0 |
| 0 | 0 | 0 | 90 | 90 | 90 | 90 | 90 | 0 | 0 |
| 0 | 0 | 0 | 90 | 90 | 90 | 90 | 90 | 0 | 0 |
| 0 | 0 | 0 | 90 | 0 | 90 | 90 | 90 | 0 | 0 |
| 0 | 0 | 0 | 90 | 90 | 90 | 90 | 90 | 0 | 0 |
| 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 0 | 0 | 90 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |

$h[.,.]$

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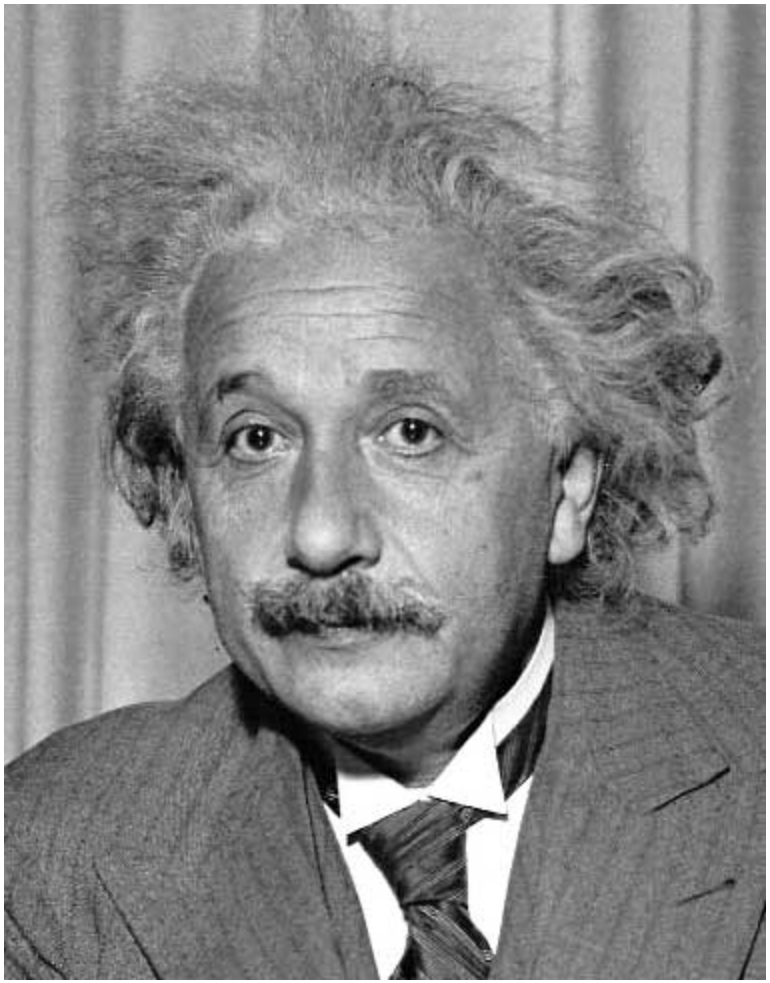
|---|---|---|---|---|---|---|---|---|---|
| | | | | | | | | | |
| | 0 | 10 | 20 | 30 | 30 | 30 | 20 | 10 | |
| | 0 | 20 | 40 | 60 | 60 | 60 | 40 | 20 | |
| | 0 | 30 | 60 | 90 | 90 | 90 | 60 | 30 | |
| | 0 | 30 | 50 | 80 | 80 | 90 | 60 | 30 | |
| | 0 | 30 | 50 | 80 | 80 | 90 | 60 | 30 | |
| | 0 | 20 | 30 | 50 | 50 | 60 | 40 | 20 | |
| | 10 | 20 | 30 | 30 | 30 | 30 | 20 | 10 | |
| | 10 | 10 | 10 | 0 | 0 | 0 | 0 | 0 | |
| | | | | | | | | | |

$$h[m,n] = \sum_{k,l} g[k,l]\, f[m+k, n+l]$$



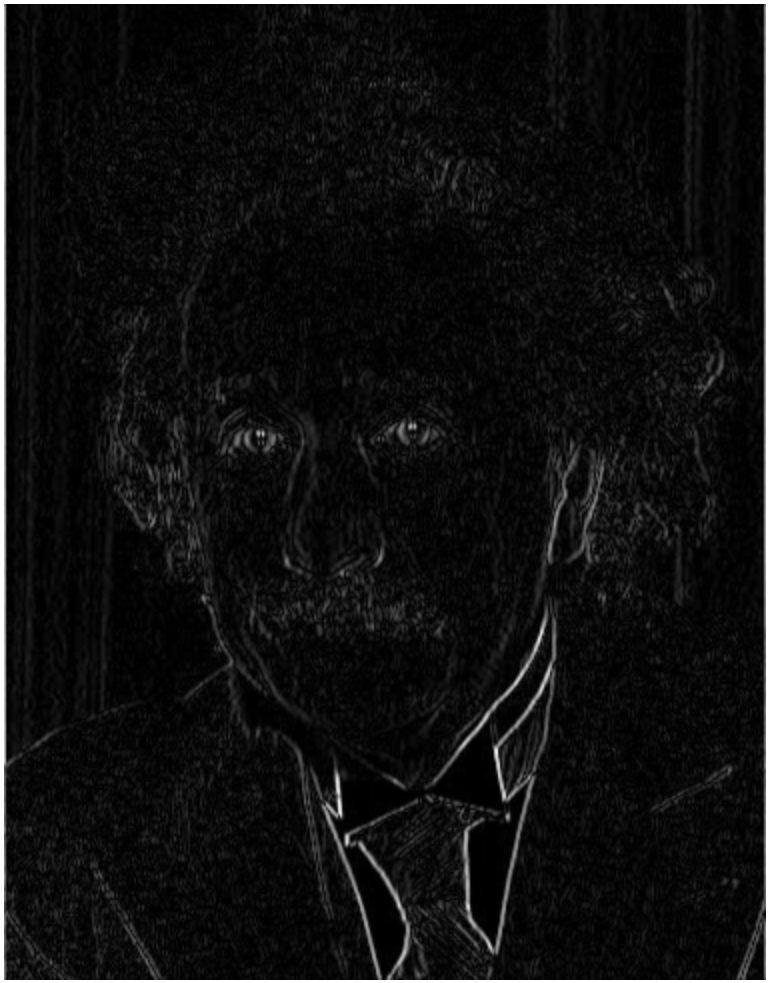
Credit: S. Seitz

# Image filtering



| | | |
|---|---|---|
| 1 | 0 | -1 |
| 2 | 0 | -2 |
| 1 | 0 | -1 |

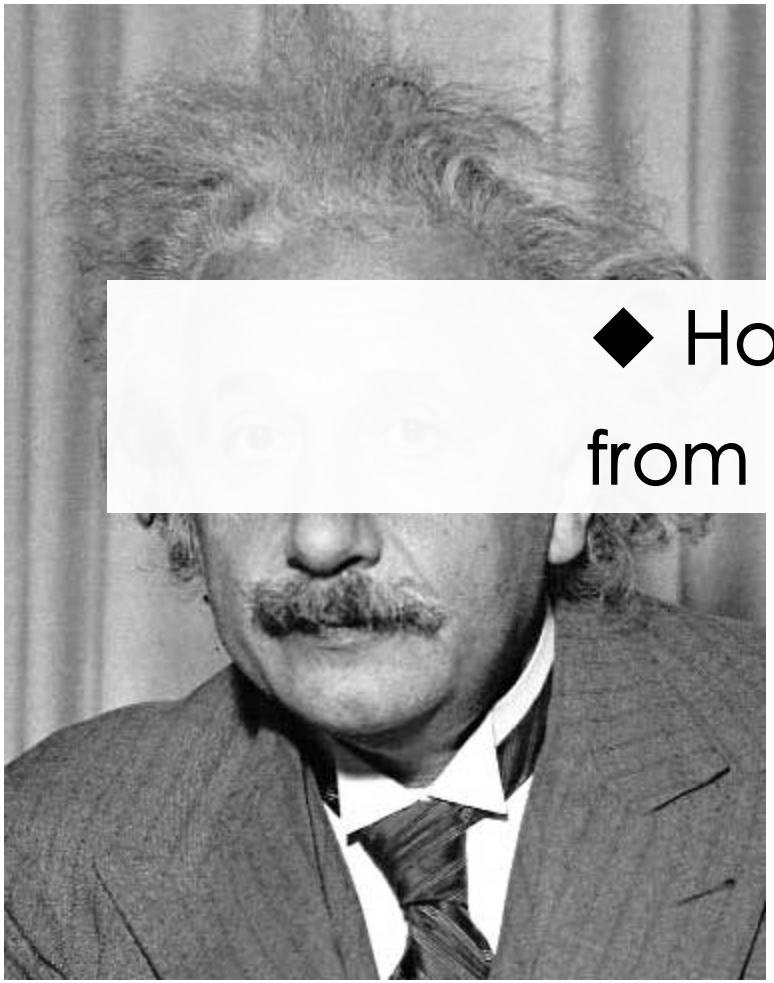
Sobel



Vertical Edge
(absolute value)

http://en.wikipedia.org/wiki/Sobel_operator

# Image filtering



- How to learn filters from Big Visual data?

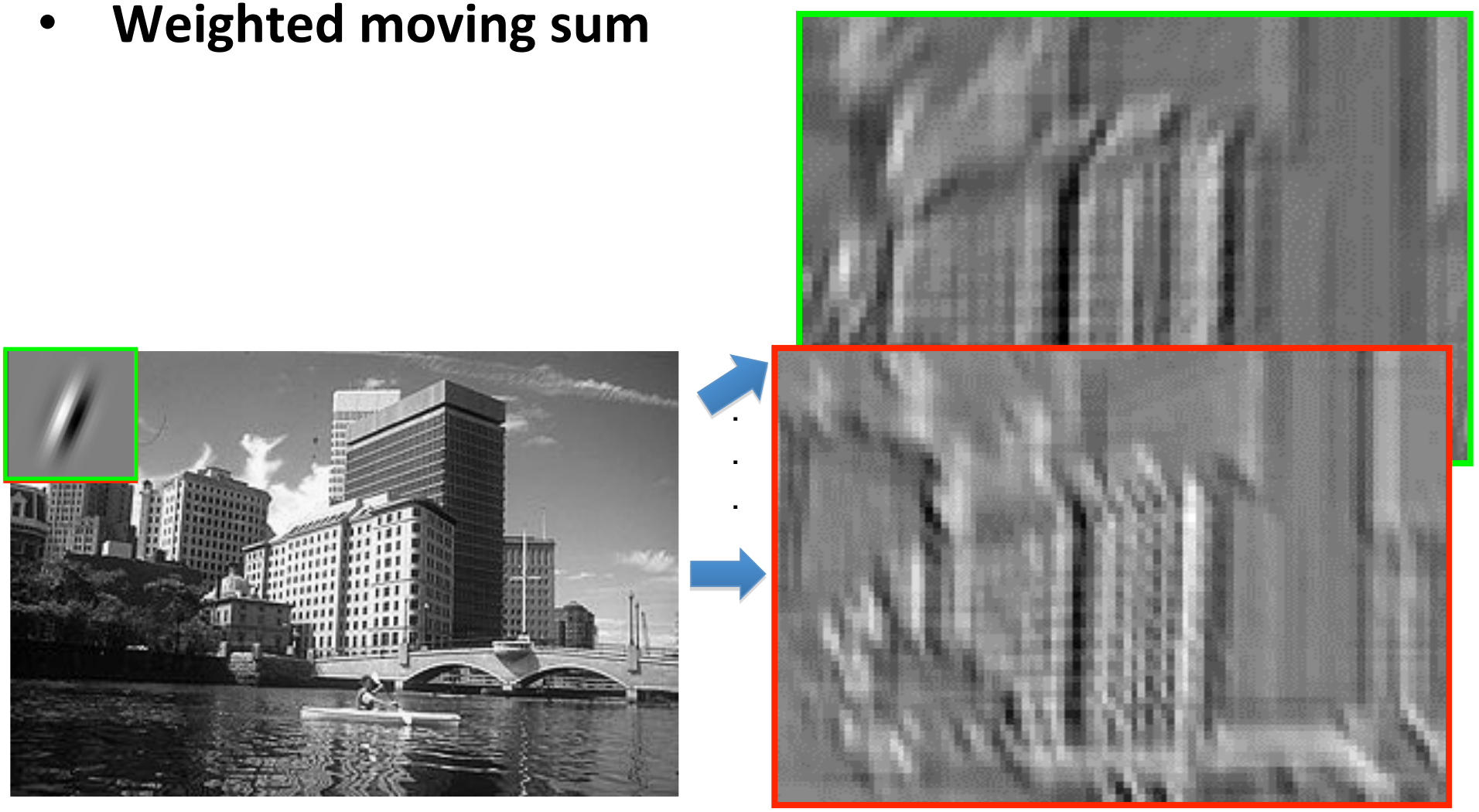
| | | |
|---|---|---|
| 0 | 0 | 0 |
| -1 | -2 | -1 |

Sobel

Horizontal Edge (absolute value)

# What is 2D Convolution?

- **Weighted moving sum**

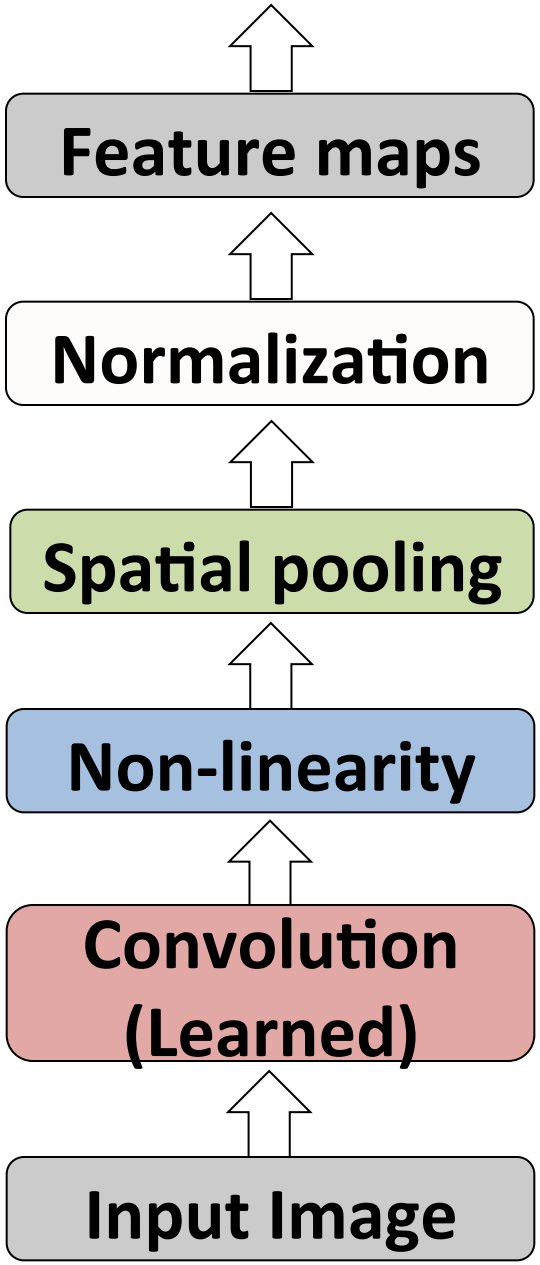


Input

Feature Activation Map

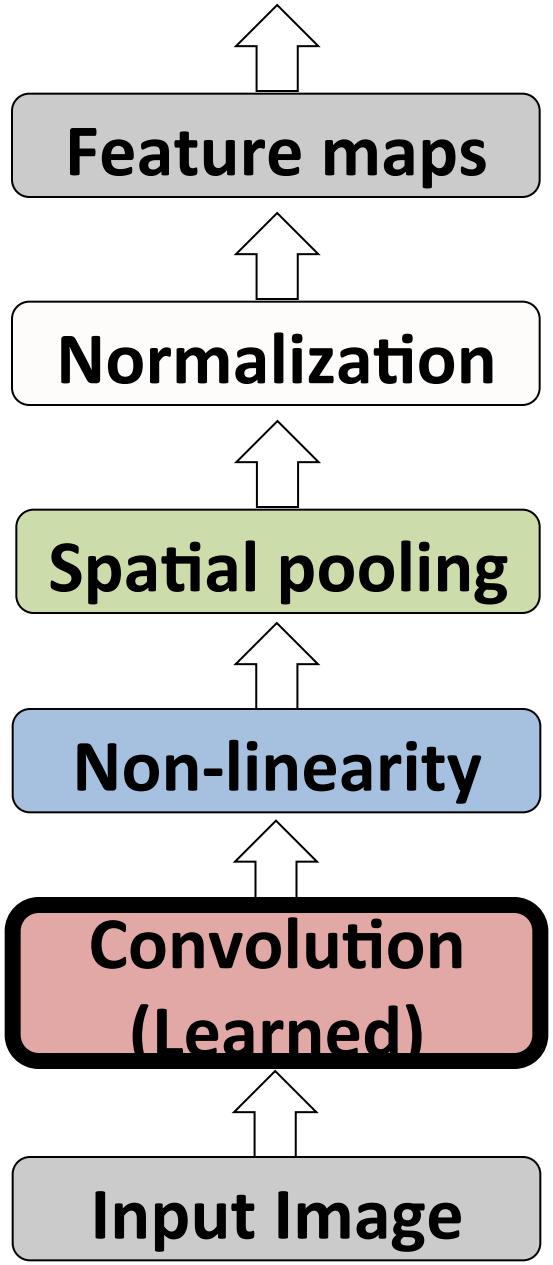
slide credit: S. Lazebnik

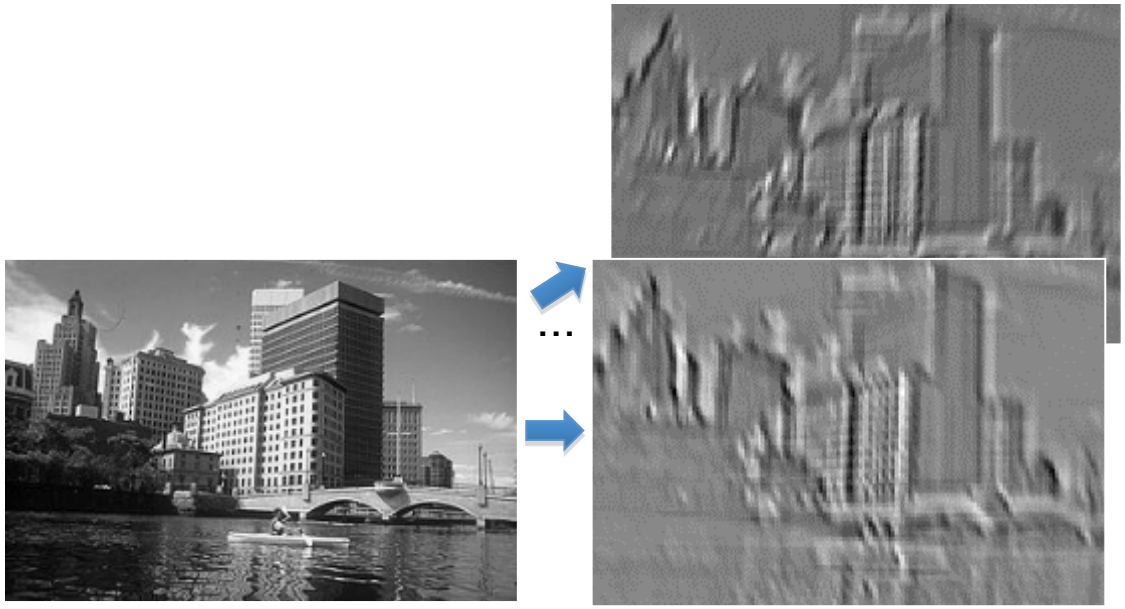
# Convolutional Neural Networks




slide credit: S. Lazebnik

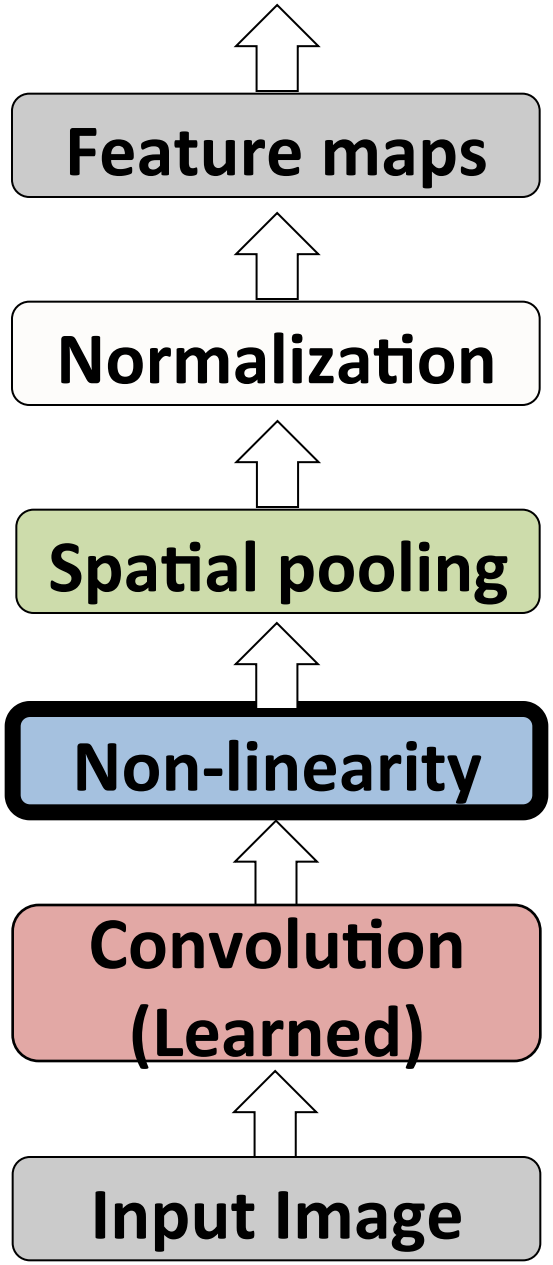
# Convolutional Neural Networks

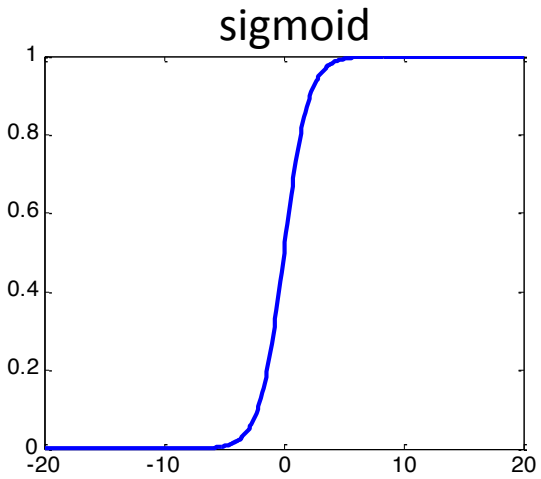


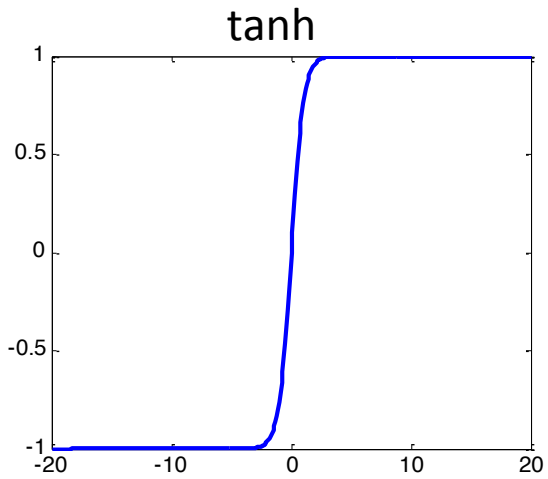




slide credit: S. Lazebnik

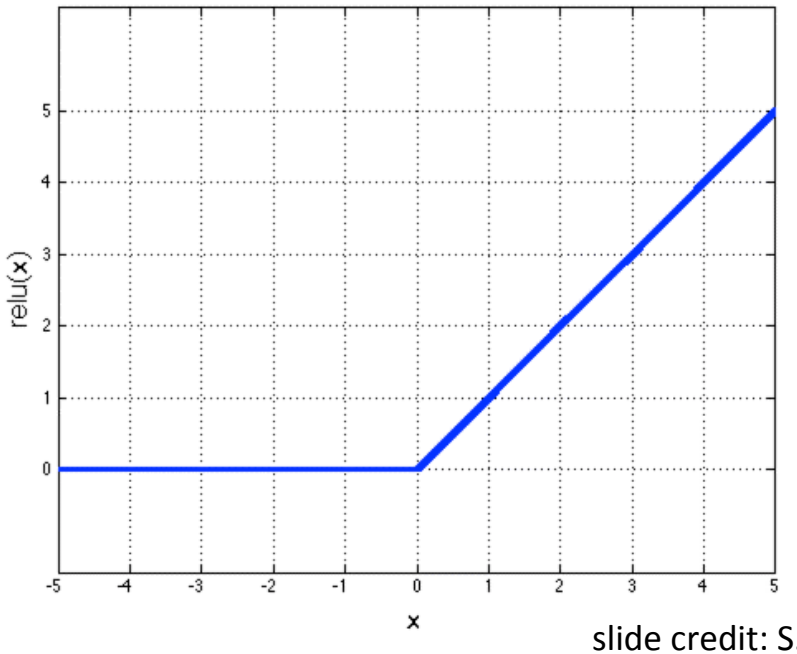
# Convolutional Neural Networks




Rectified Linear Unit (ReLU)




slide credit: S. Lazebnik

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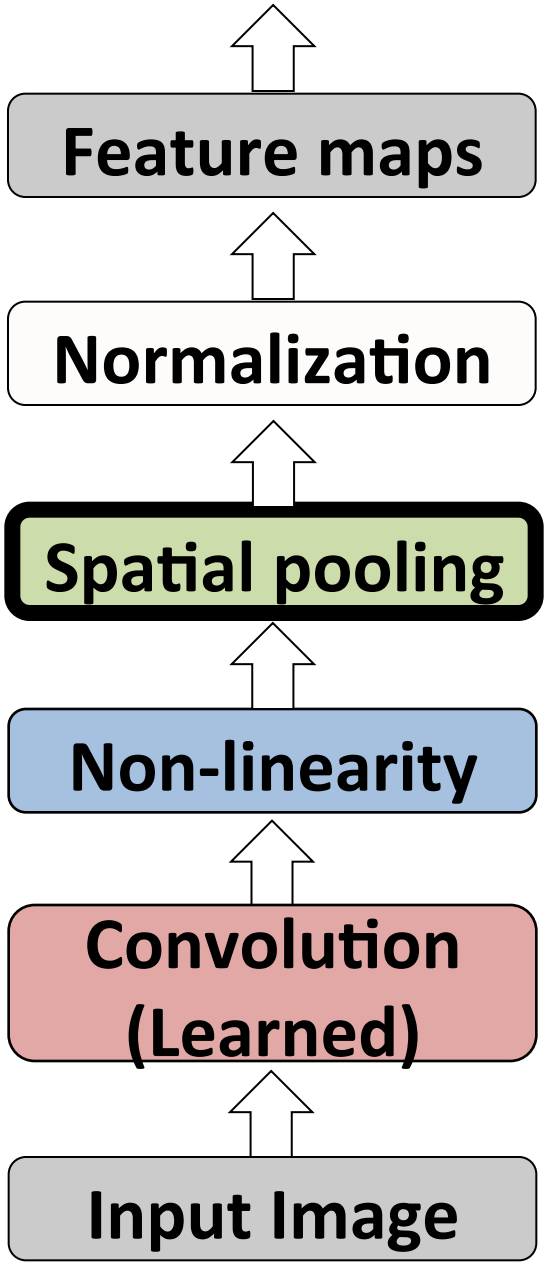
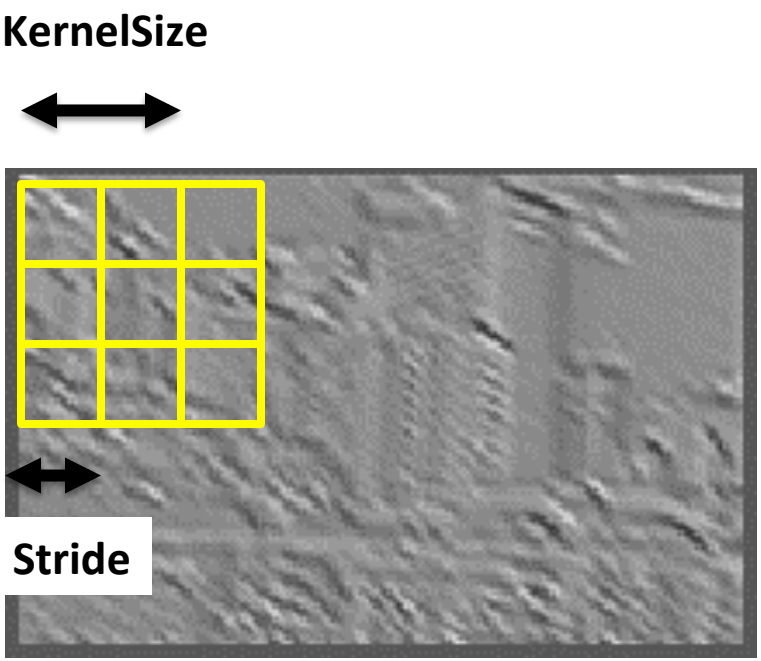
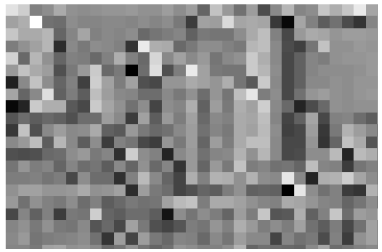



Max pooling

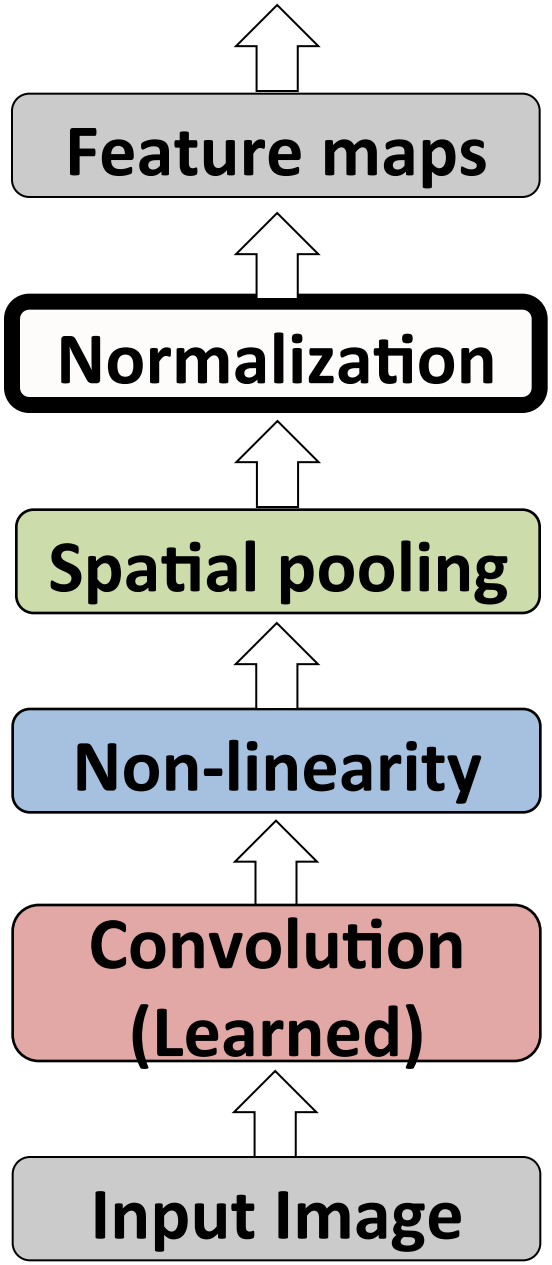


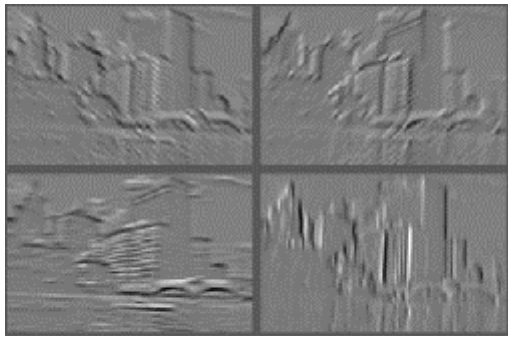
Max-pooling:
a **non-linear** down-sampling

Provide *translation invariance*

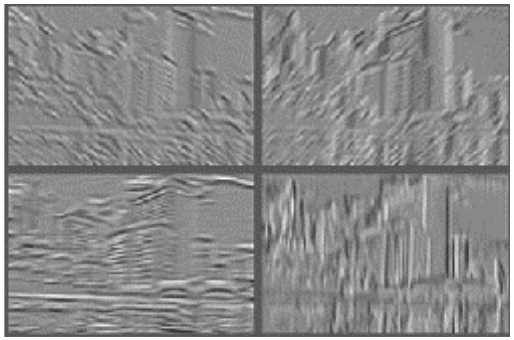
slide credit: S. Lazebnik

# Convolutional Neural Networks



Feature Maps



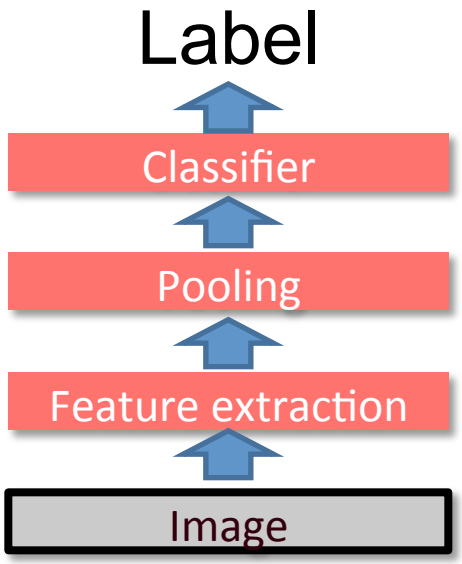
Feature Maps After Contrast Normalization

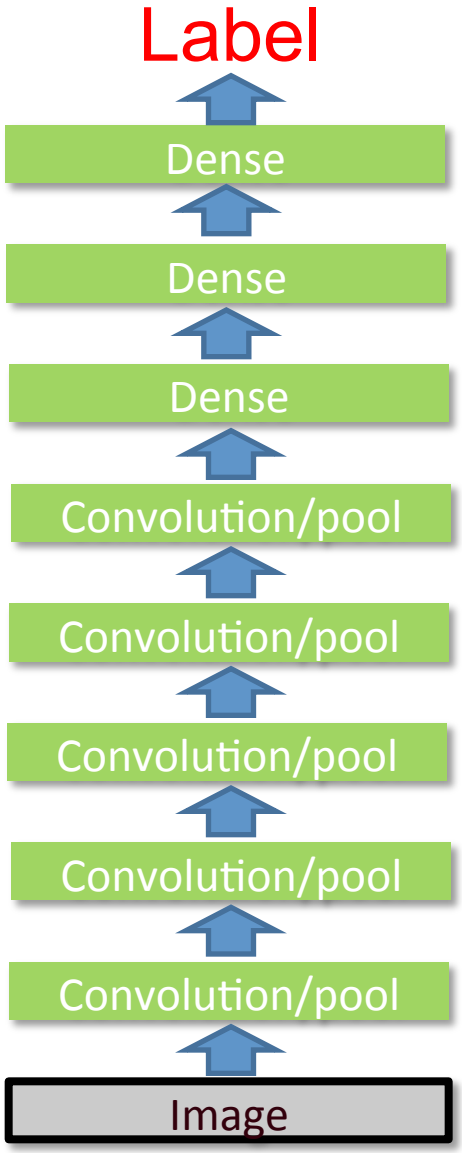
Equalizes the feature maps locally: weak signals are boosted, whereas strong signals are suppressed.

slide credit: S. Lazebnik

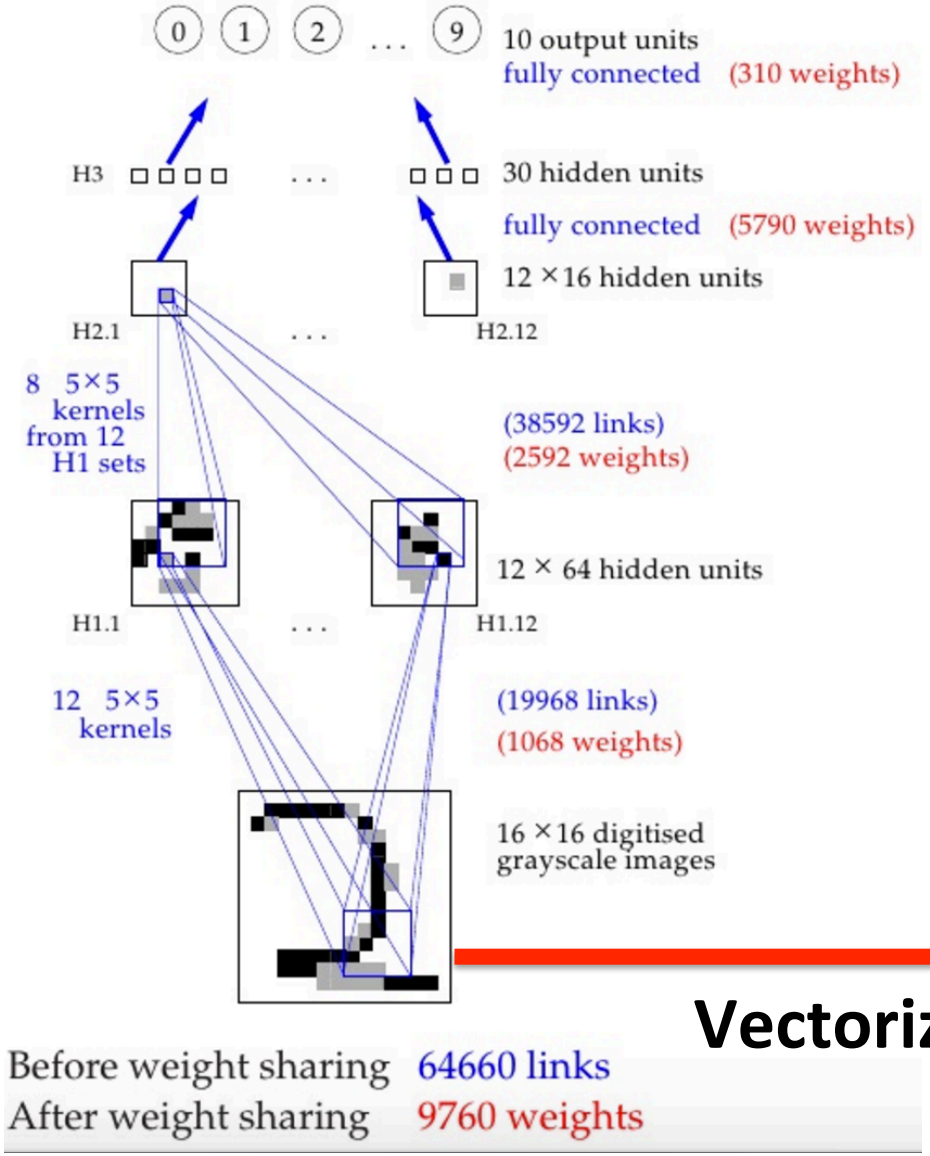
# Engineered vs. learned features

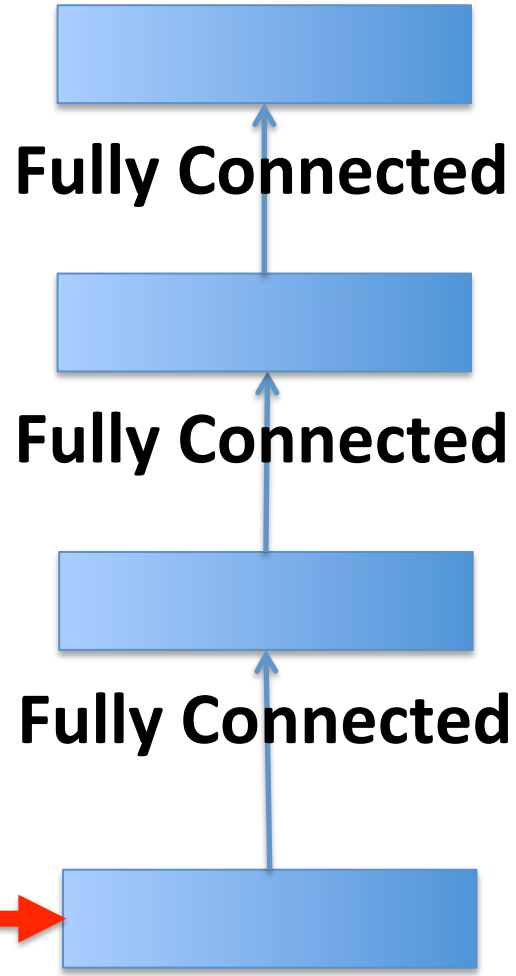
Convolutional filters are trained in a supervised manner by back-propagating classification error



# Why Convolution?



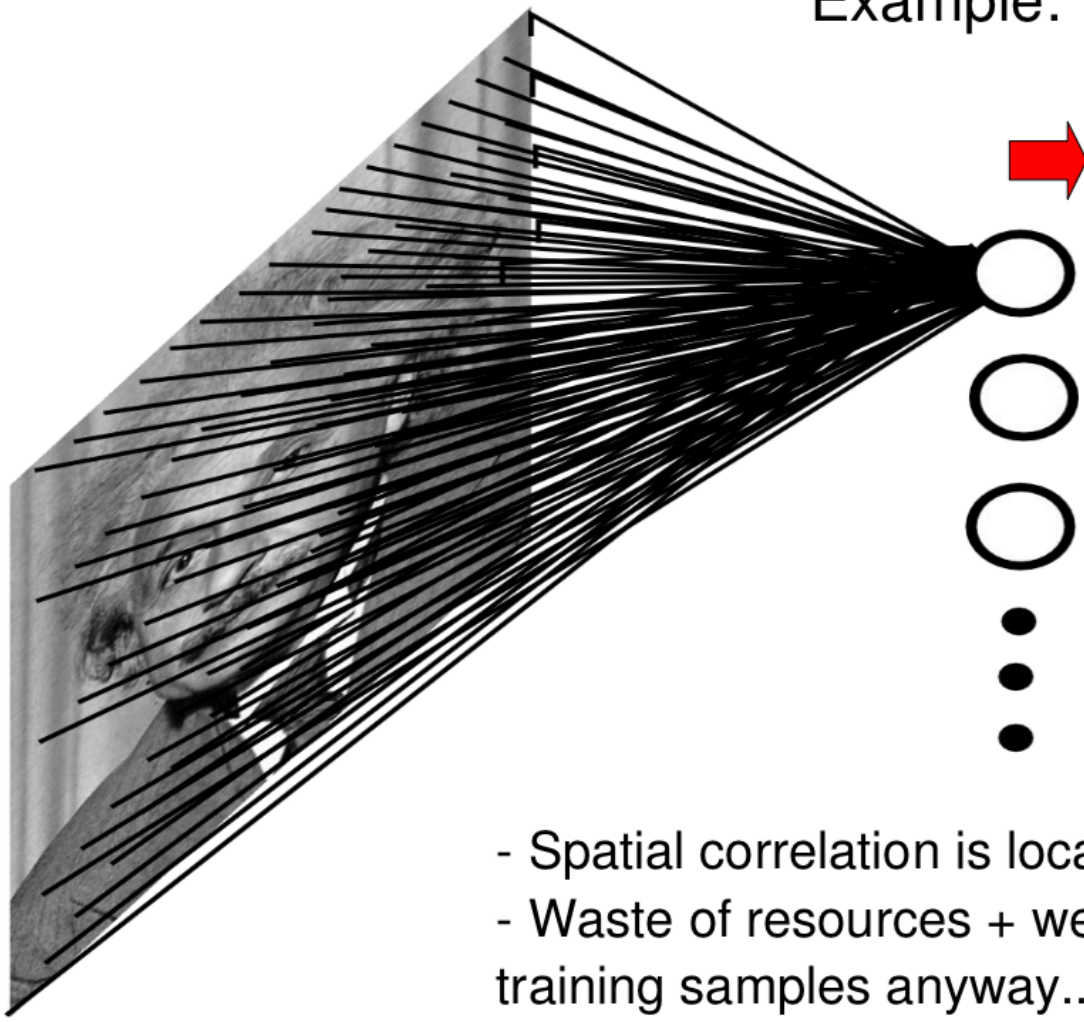




Vectorize

16x16=256

Yann Lecun, 1989

# Fully Connected Layer



Example: 200x200 image

40K hidden units

**~2B parameters**!!!

- Spatial correlation is local
- Waste of resources + we have not enough training samples anyway..