Artificial Neural Networks: Intro

"Making Connections" by Filomena Booth (2013)

SML310: Research Projects in Data Science, Fall 2019

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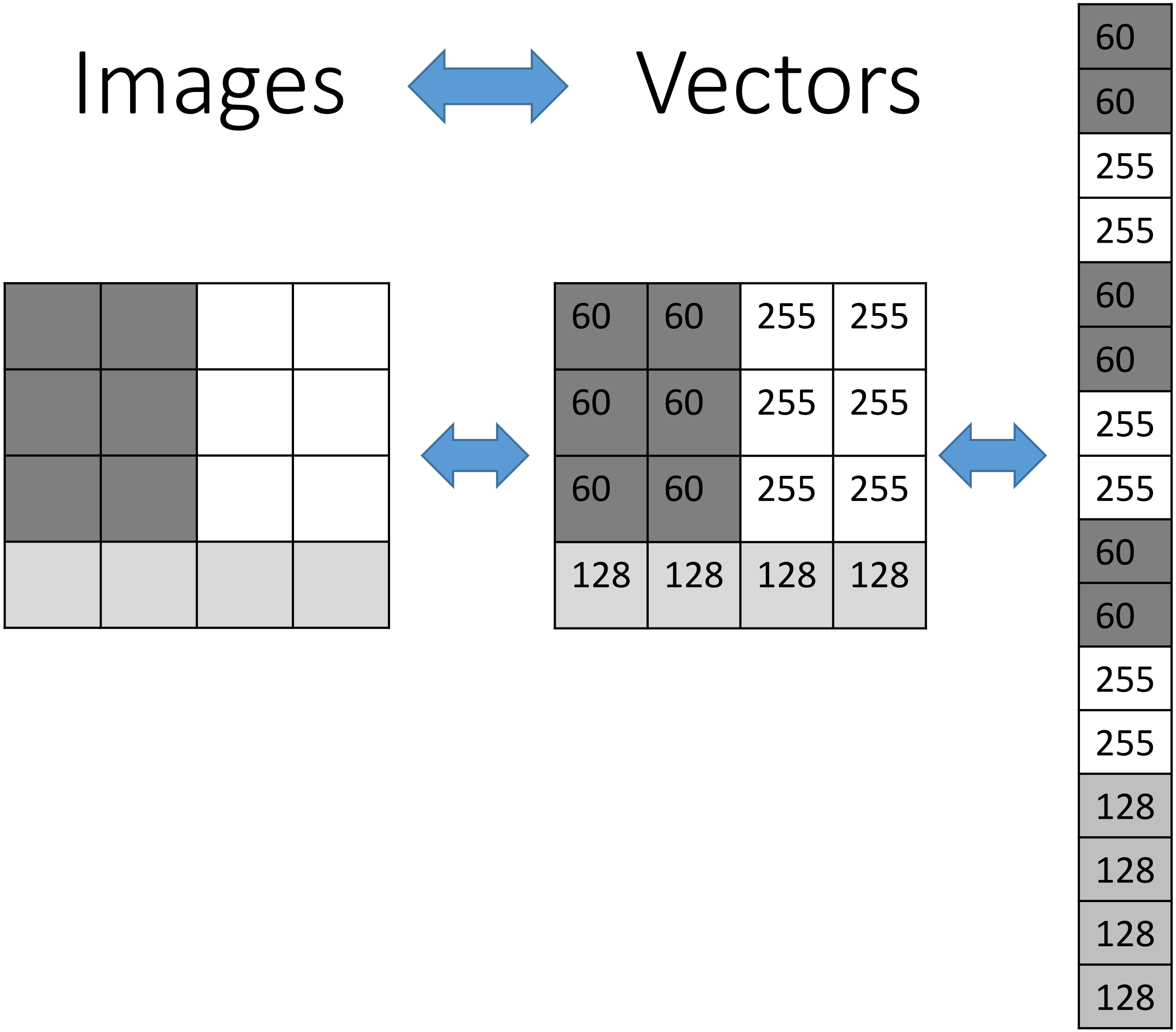
Sample task

- Training set: 6 actors, with 100 64×64 photos of faces for each
- Test set: photos of faces of the same 6 actors
- Want to classify each face as one of ['Fran Drescher', 'America Ferrera', 'Kristin Chenoweth', 'Alec Baldwin', 'Bill Hader', 'Steve Carell']


Images
Vectors
60 60 255 255
60 60 255 255
60 60 255 255
128 128 128 128
60
60
255
255
60
60
255
255
60
60
255
255
128
128
128
128

The Face Recognition Task

- Training set:
  - $\{(x^{(1)}, y^{(1)}), (x^{(2)}, y^{(2)}), \ldots, (x^{(N)}, y^{(N)})\}$
    - $x^{(i)}$ is a k-dimensional vector consisting of the intensities of all the pixels in in the i-th photo (20×20 photo $\rightarrow x^{(i)}$ is 400-dimensional)
    - $y^{(i)}$ is the *label* (i.e., name)
- Test phase:
  - We have an input vector x, and want to assign a label y to it
    - Whose photo is it?

Reminder: Face Recognition using 1-Nearest Neighbors (1NN)

- Training set: $\left\{\left(x^{(1)}, y^{(1)}\right), \left(x^{(2)}, y^{(2)}\right), \dots, \left(x^{(N)}, y^{(N)}\right)\right\}$
- Input: x
- 1-Nearest Neighbor algorithm:
  - Find the training photo/vector $x^{(i)}$ that's as "close" as possible to x, and output the label $y^{(i)}$

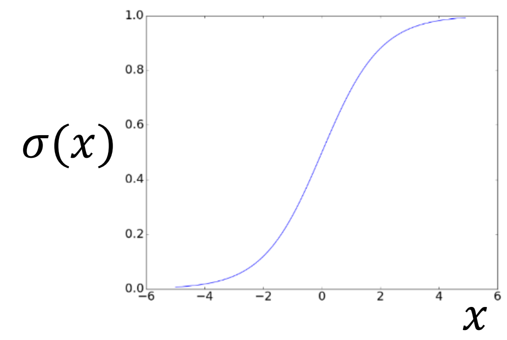
Input x

Closest training image to the input x

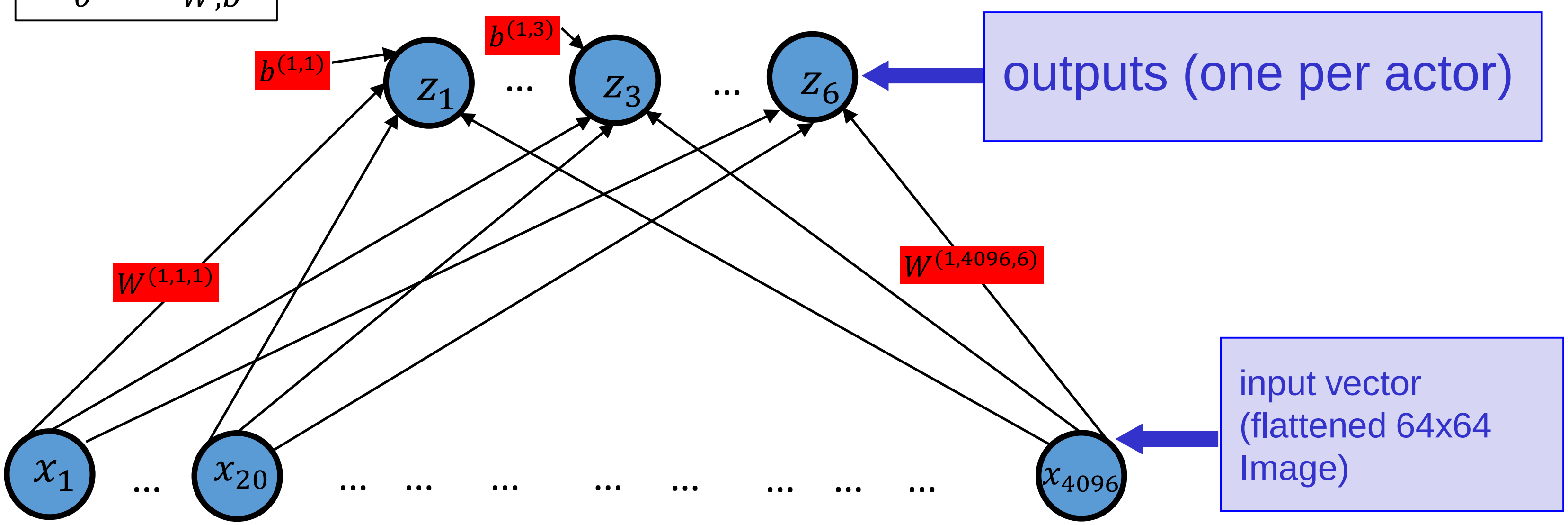
Output: Paul

The Simplest Possible Neural Network for Face Recognition

$$z_k = \sigma\left(\sum_{j=1}^{4096} W^{(1,j,k)}\, x_j + b^{(1,k)}\right)$$
$$= \sigma\left(W^{(1,*,k)} \cdot x + b^{(1,k)}\right)$$

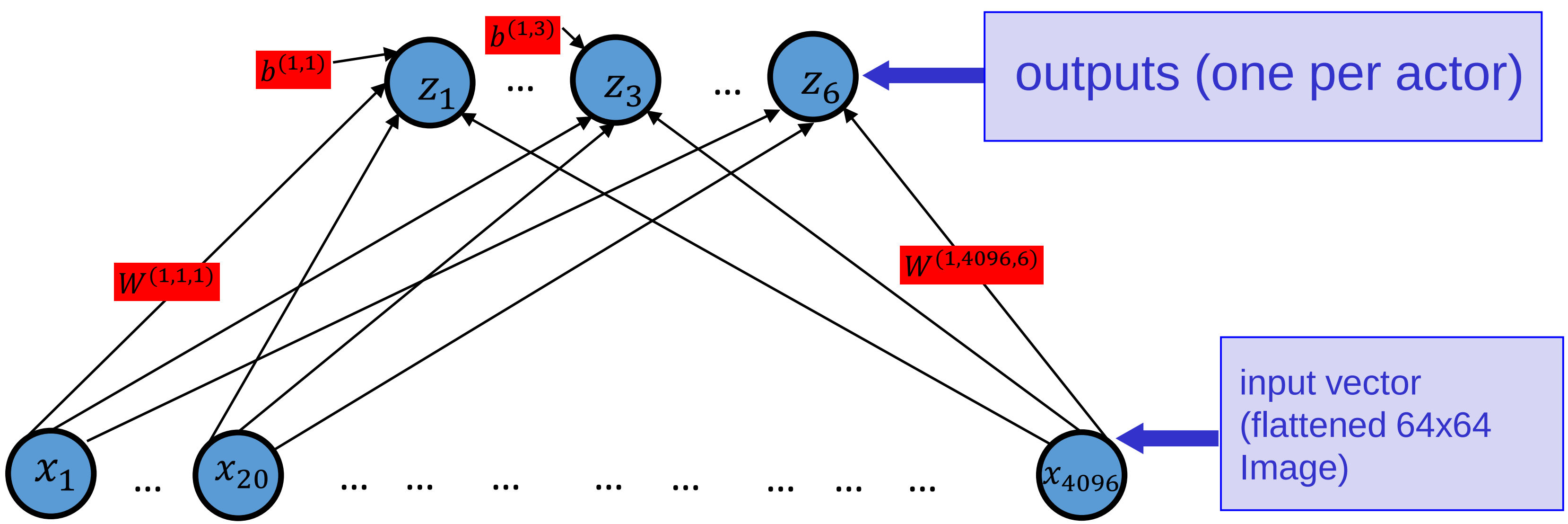


$$\boxed{h_\theta = h_{W,b}}$$



Training a neural network

- Adjust the W's (4096 × 6 coefs) and b's (6 coefs)
  - Try to make it so that if
    x is an image of actor 1, z is as close as possible to (1, 0, 0, 0, 0, 0)
    x is an image of actor 2, z is as close as possible to (0, 1, 0, 0, 0, 0)
    ……



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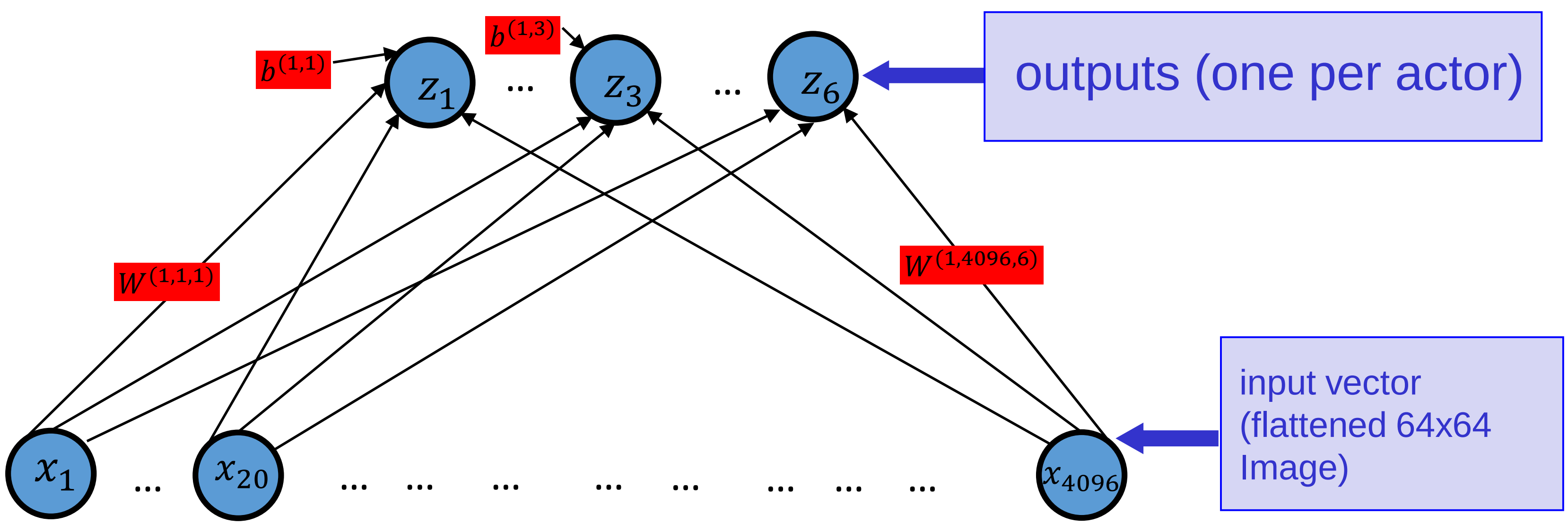
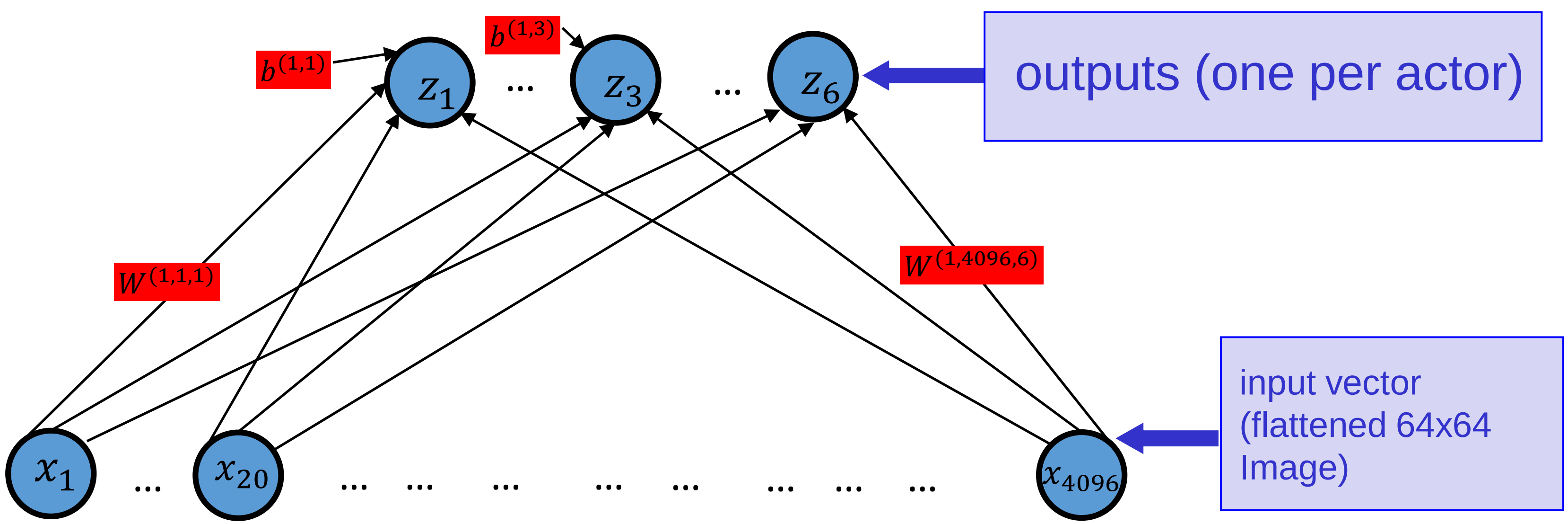


Face recognition

- Compute the z for a new image x
- If z_k is the largest output, output name k



An interpretation

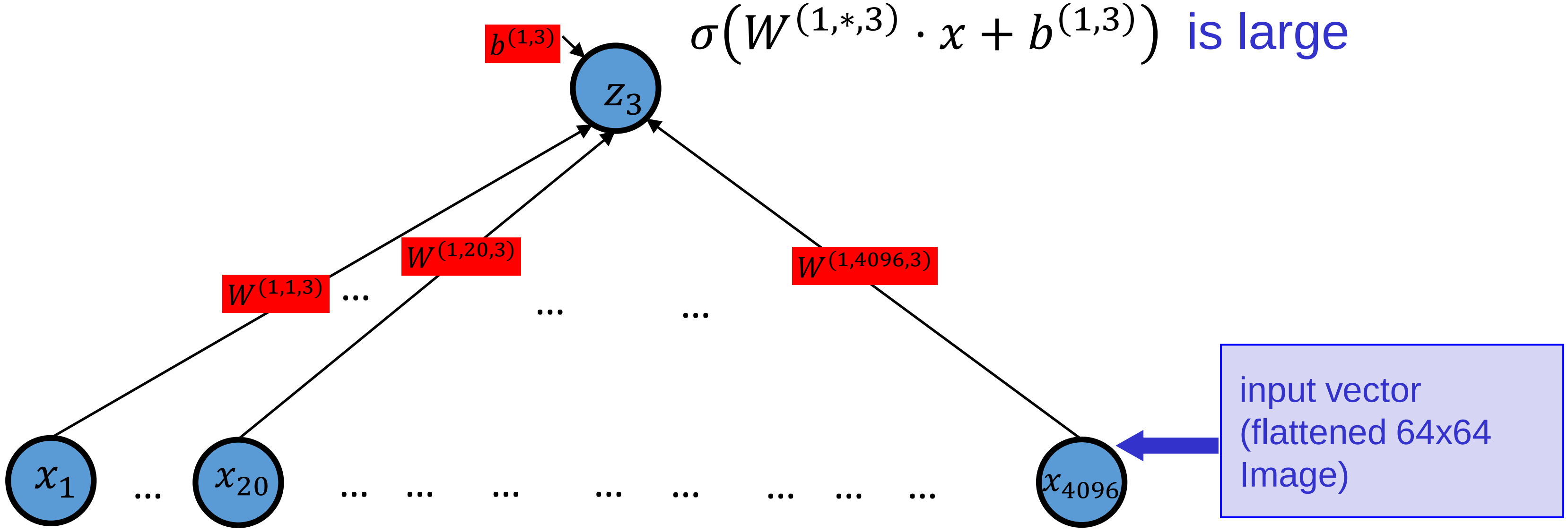
z_1 is large if $W^{(1,*,1)} \cdot x$ is large
z_2 is large if $W^{(1,*,2)} \cdot x$ is large

z_3 is large if $W^{(1,*,3)} \cdot x$ is large

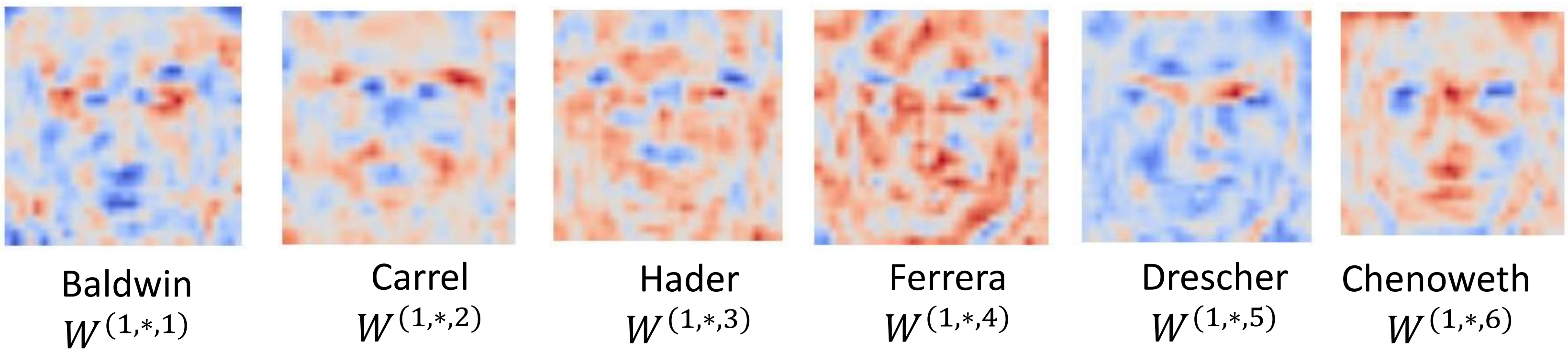
....

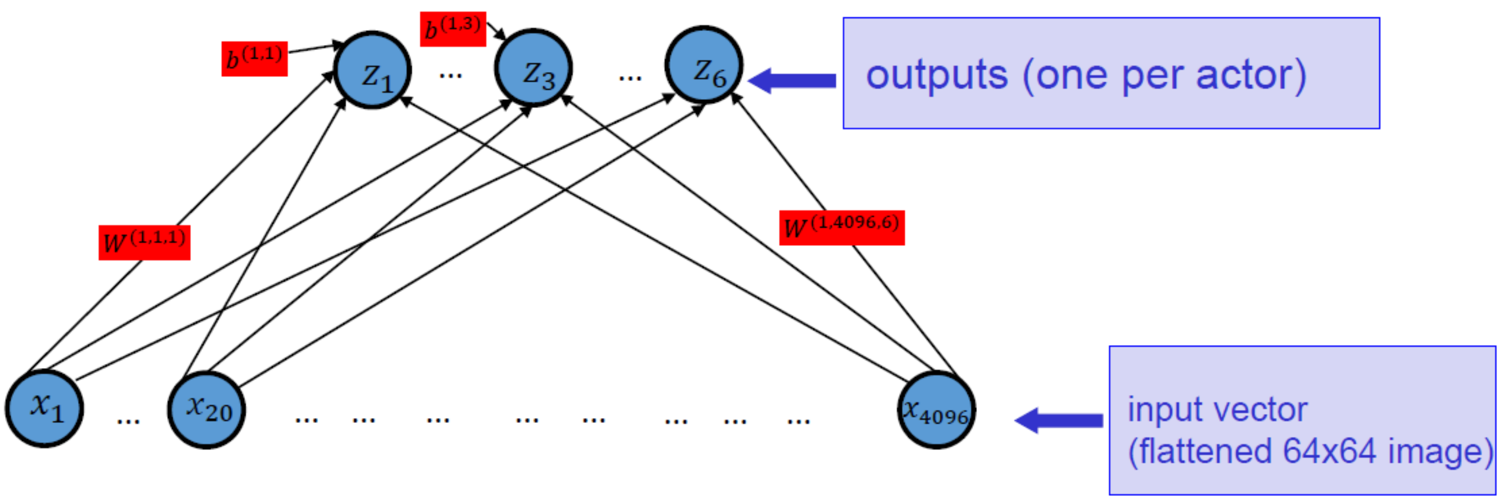
$W^{(1,*,1)}, W^{(1,*,2)}, \ldots, W^{(1,*,6)}$ are *templates* for the faces of actor 1, actor 2, …, actor 6

Actor 3 neuron activated:
$\sigma\left(W^{(1,*,3)} \cdot x + b^{(1,3)}\right)$ is large

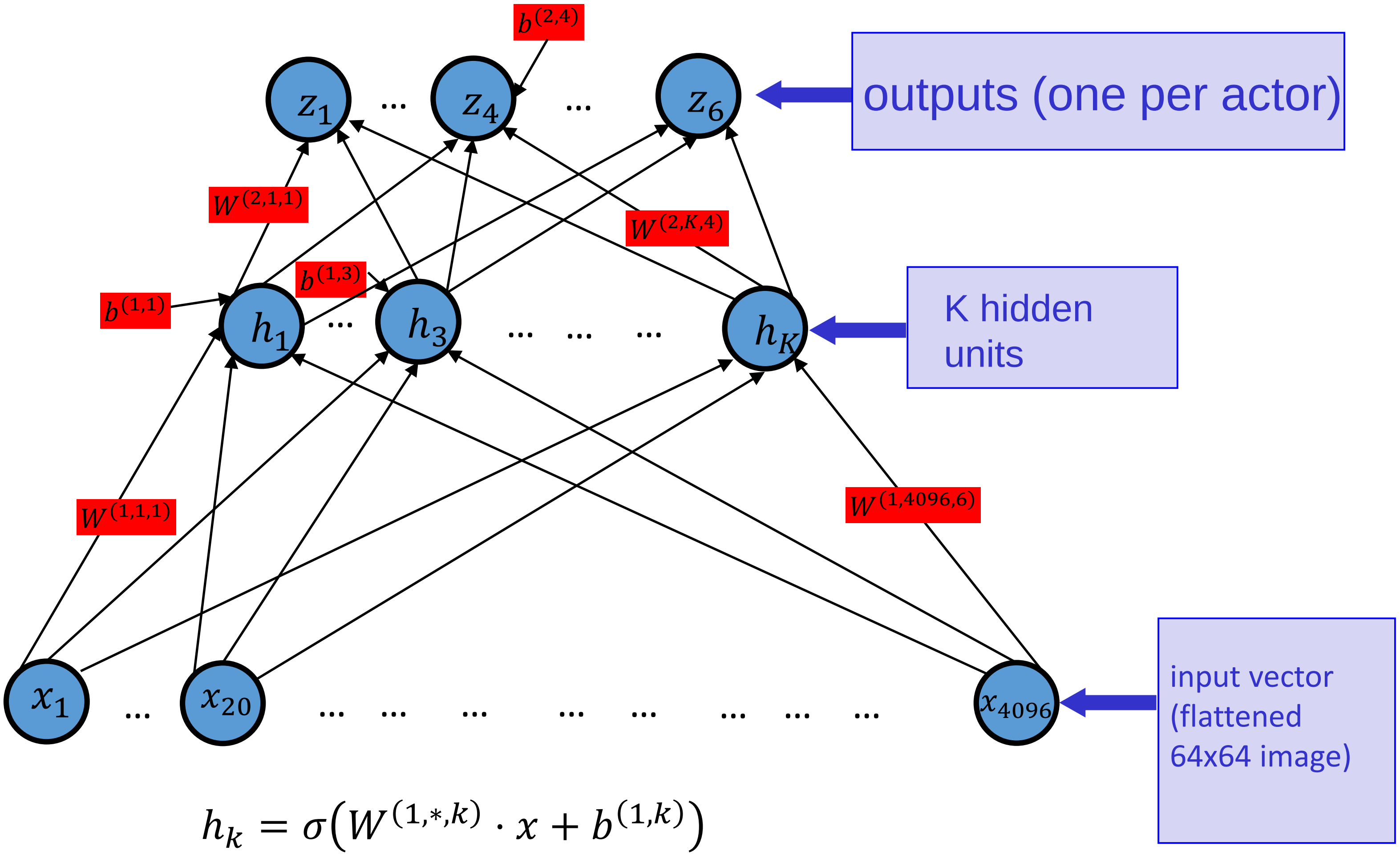


Visualizing the parameters W





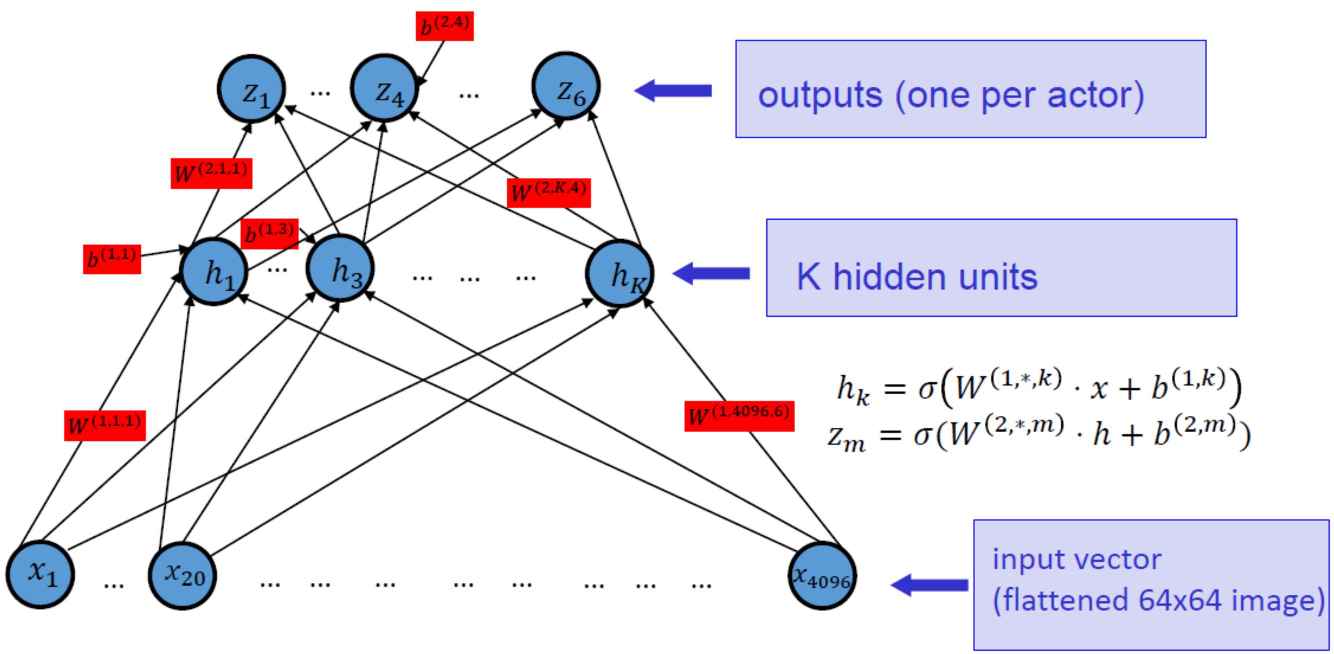
Deep Neural Networks: Introducing Hidden Layers



$$h_k = \sigma\left(W^{(1,*,k)} \cdot x + b^{(1,k)}\right)$$
$$z_m = \sigma(W^{(2,*,m)} \cdot h + b^{(2,m)})$$

Why a hidden layer?

- Instead of checking whether x looks like one of 6 templates, we'll be checking whether x looks like one of K templates, for a large K



Recap: Face Recognition with ML

- 1-Nearest-Neighbor: match x to all the images in the training set
- 0-hidden-layer neural network*: match x to several templates, with one template per actor
  - The templates work better than any individual photo
- 1-hidden-layer neural network: match x to K templates
  - The templates work better than any individual photo
  - More templates means better accuracy on the training set

*A.K.A. multinomial logistic regression to its friends

Visualizing a One-Hidden-Layer NN

Demo

http://playground.tensorflow.org/

Deep Neural Networks as a Model of Computation

- Most people's first instinct a face classifier is to write a complicated computer program
- A deep neural network *is* a computer program:

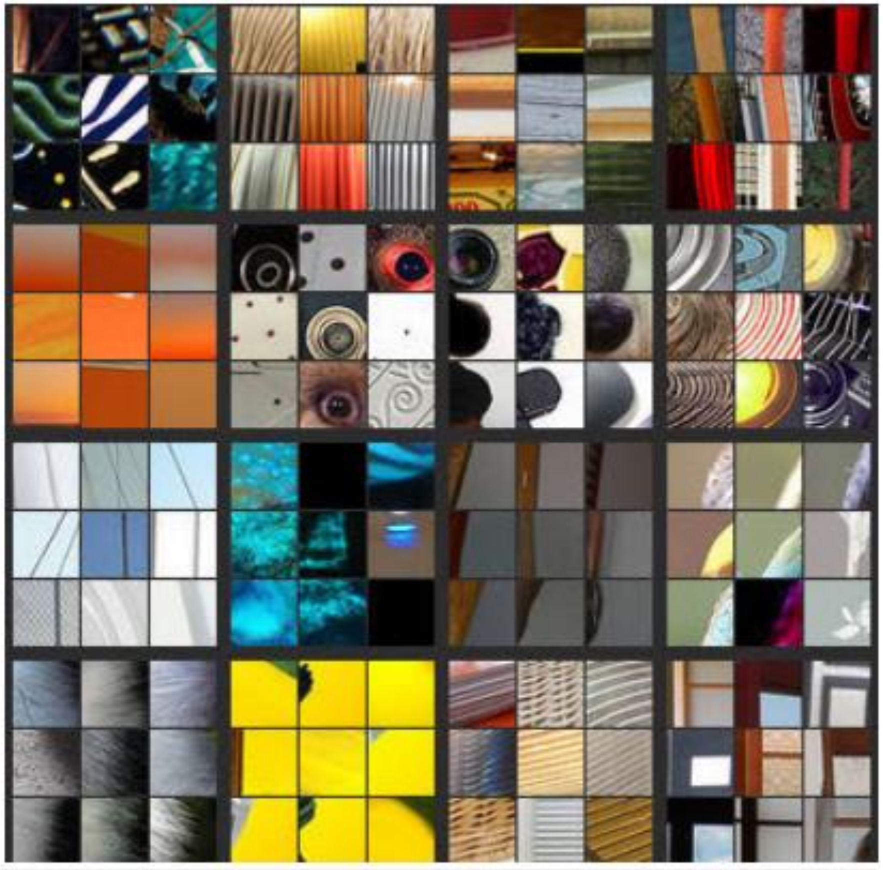
```
h1 = f1(x)
h2 = f2(h1)
h3 = f3(h2)
…
h9 = f9(h8)
```

- Can think of every layer of a neural network as one step of a parallel computation
- Features/templates are the functions that are applied to the previous layers
- Learning features ⇔ Learning what function to apply at step t of the algorithm

What are the hidden units doing?

- Find the images in the dataset that activate the units the *most*
- *Let's see some visualizations of neurons of a large deep network trained to recognize objects in images*
    - Then network classifies images as one of 1000 objects (sample objects: toy poodle, flute, forklift, goldfish…)
    - The network has 8 layers
    - Note: more tricks were used in designing the networks than we have time to mention! In particular, a convolutional architecture is crucial

Units in Layer 3



Matthew Zeiler and Rob Fergus, “Visualizing and Understanding Convolutional Networks” (ECCV 2014)

Units in Layer 4

Matthew Zeiler and Rob Fergus, “Visualizing and Understanding Convolutional Networks” (ECCV 2014)

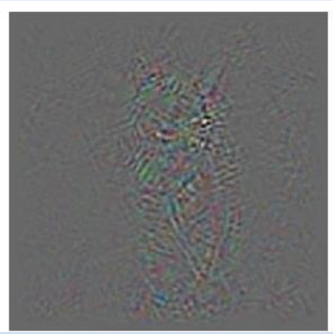
Units in Layer 5

Matthew Zeiler and Rob Fergus, "Visualizing and Understanding Convolutional Networks" (ECCV 2014)

Which pixels are responsible for the output?

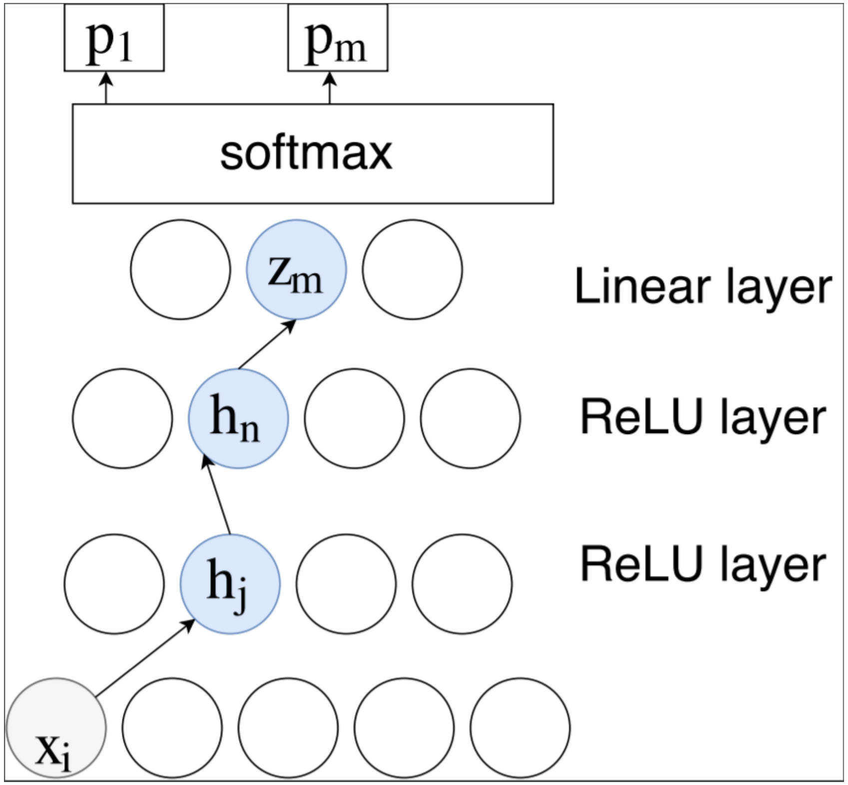
- For each pixel in a particular image ask:
  - If I changed this pixel j by a little bit, how would that influence the output i
  - Equivalent to asking: what's the gradient $\frac{\partial output_i}{\partial input_j}$
  - We can visualize why a particular output was chosen by the network by computing $\frac{\partial output_i}{\partial input_j}$ for every j, and displaying that as an image

Gradient and Guided Backpropagation

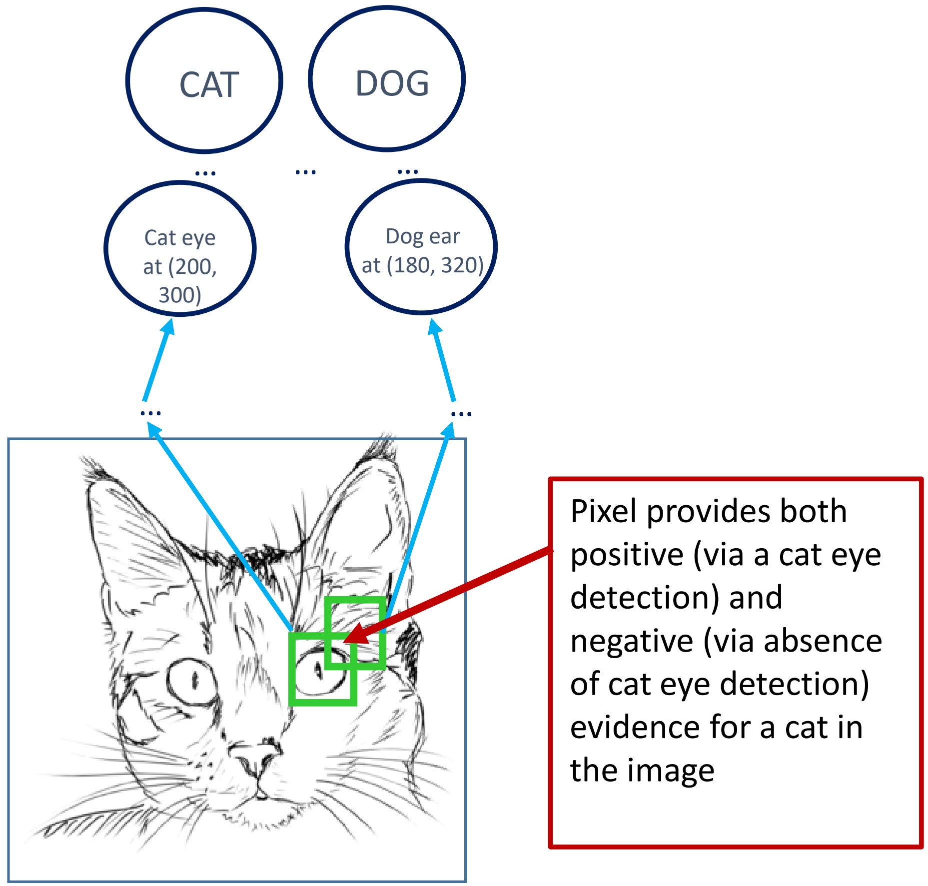
Image I	
$\dfrac{\partial \text{Cat-Neuron}}{\partial I}$	
Guided Backpropagation visualization	

Guided backpropagation

- Instead of computing $\frac{\partial p_m}{\partial x}$, only consider paths from x to p_m where the weights are positive and all the units are positive (and greater than 0). Compute this modified version of $\frac{\partial p_m}{\partial x}$
- Only consider evidence for neurons being active, discard evidence for neurons having to be not active

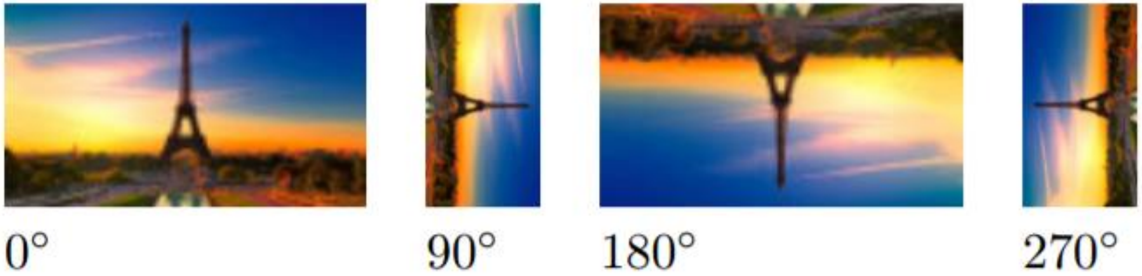


Guided Backpropagation Intuition

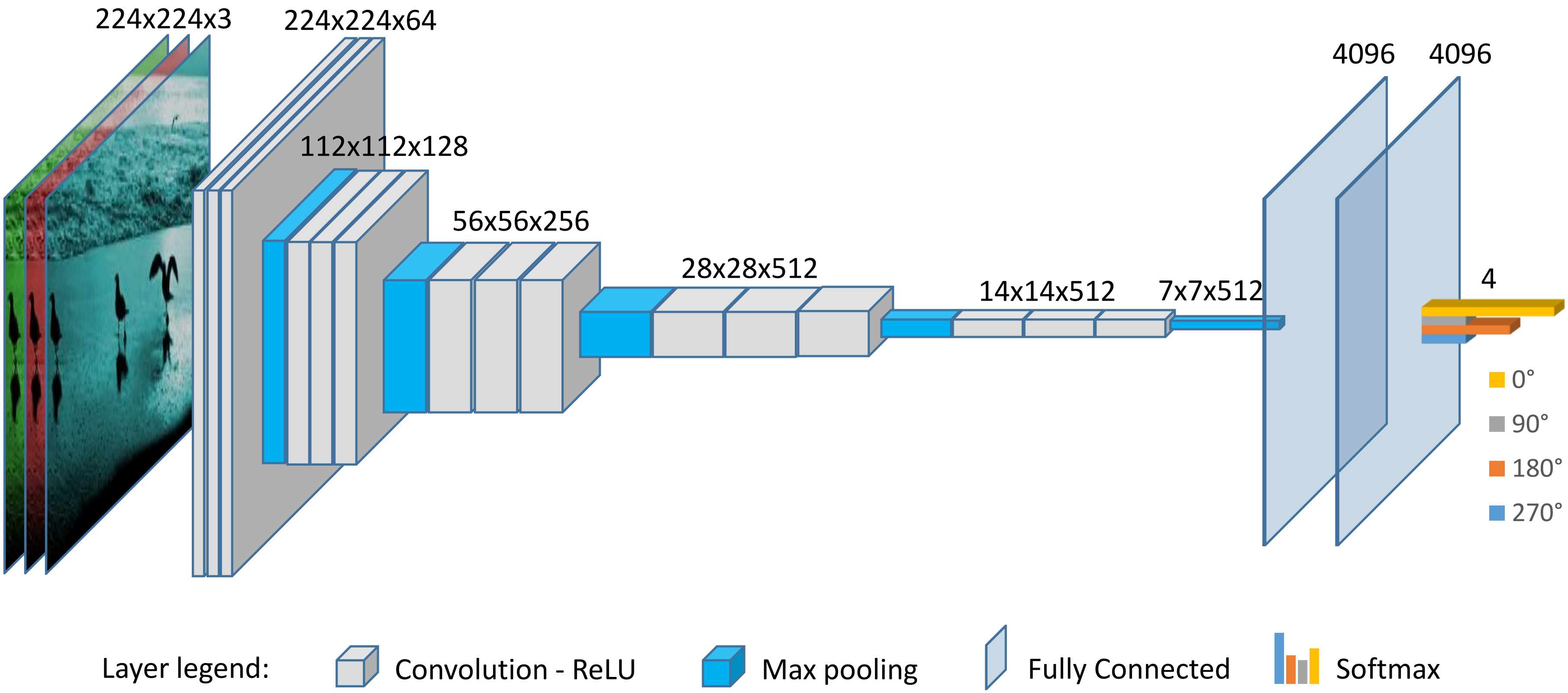


Application: Photo Orientation

- Detect the correct orientation of a consumer photograph
- Input photo is rotated by 0°, 90°, 180° or 270°
- Help speed up the digitization of analog photos
- Need correctly oriented photos as inputs for other systems

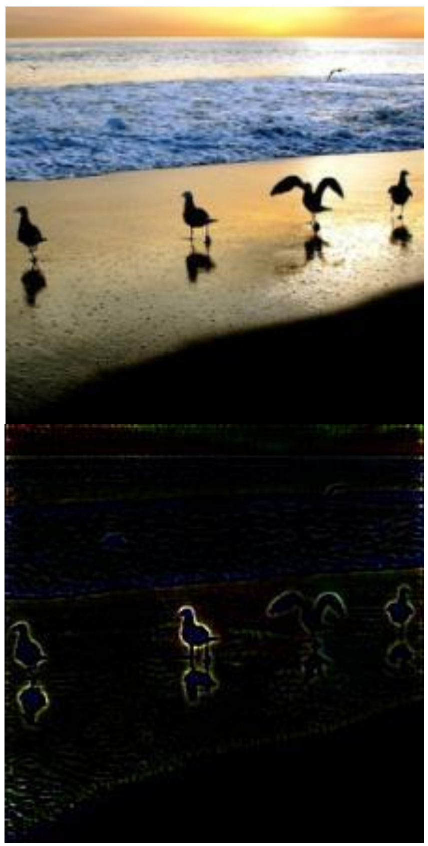


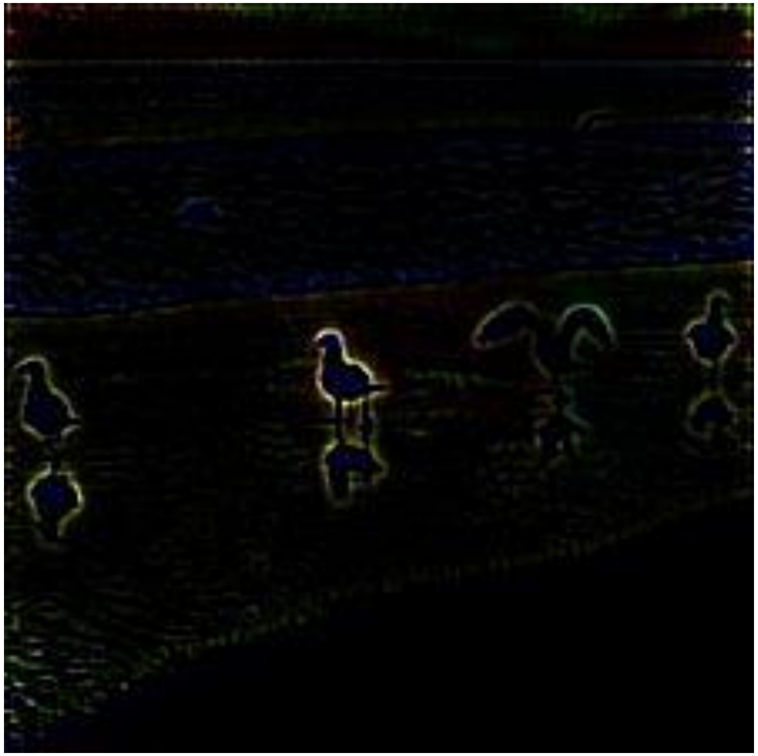
A Neural Network for Photo Orientation



Correctly Oriented Photos

- Display pixels that provide direct positive evidence for 0°





Incorrectly-oriented photos