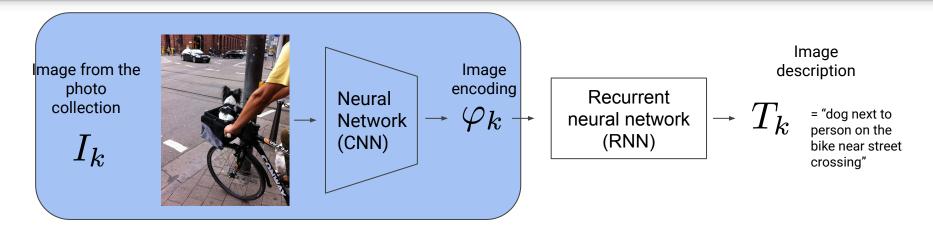
# Sapienza Training Camp 2020

Building an Image Search Engine

3 - 5 September, 2020

# Roadmap



Q Query: "person walking with a dog on the beach"

Define similarity function. Order images according to similarity to the query.

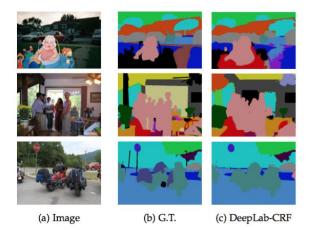
$$\sin(Q, T_1) > \sin(Q, T_2)$$

# Agenda for today

- Introduction to Neural Networks
- Convolutional Neural Networks (CNN)
- Modern CNN Architectures

### **Computer Vision**





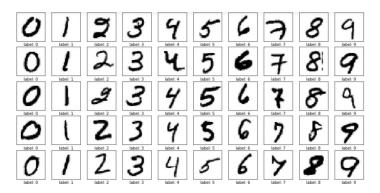






## Neural Networks Recap

- Let's start with a simple neural network from the self-study tutorial
- The task is to recognize handwritten digits



### Neural Networks Recap

#### Basic model from the self-study course:

https://codelabs.developers.google.com/codelabs/cloud-tensorflow-mnist

## Computation within a single neuron

 Basic building block: single neuron

$$a = \sum_{i=1}^{D} w_i x_i + w_0$$

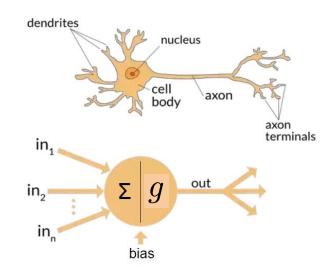


Image from https://towardsdatascience.com/the-differences-between-artificia l-and-biological-neural-networks-a8b46db828b7

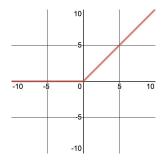
## Computation within a single neuron

Activation function

$$h = g(a)$$

ReLU activation function:

$$g(a) = \max(a, 0)$$



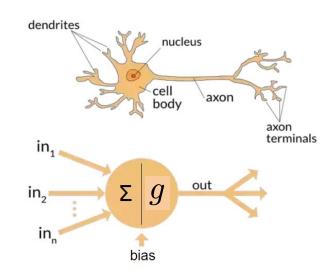


Image from https://towardsdatascience.com/the-differences-between-artificia l-and-biological-neural-networks-a8b46db828b7

# Computation within a single neuron

#### One neuron:

$$a = \sum_{i=1}^{D} w_i x_i + w_0$$
  $a = \mathbf{w}^{\top} \mathbf{x}$   $\mathbf{x} = [x_1, \dots, x_D, 1]$ 

# Single layer with multiple neurons

Let's add more neurons:

$$a_{\mathbf{k}} = \sum_{i=1}^{D} w_{\mathbf{k}i} x_i + w_{\mathbf{k}0}$$
 
$$a_{\mathbf{k}} = \mathbf{w}_{\mathbf{k}}^{\mathsf{T}} \mathbf{x}$$
 
$$\mathbf{x} = [x_1, \dots, x_D, 1]$$

# Single layer with multiple neurons

Rewrite as matrix multiplication and add ReLU non-linearity:

$$\mathbf{a} = W\mathbf{x}, \quad W \in \mathbb{R}^{200 \times 785}$$
 $h_i = \max(a_i, 0), \quad i = 1, \dots, 200$ 

### Multiple layers

Feed output as input to the next layer:

$$\mathbf{a}^{(k)} = W^{(k)} \mathbf{h}_{k-1}, \quad W \in \mathbb{R}^{N_k \times N_{k-1}}$$
$$h_i^{(k)} = \max(a_i^{(k)}, 0), \quad i = 1, \dots, N_k$$

## Final layer with softmax activation

Last layer should generate a 10-dimensional vector with probability of each digit

$$\mathbf{a}^{(k)} = W^{(k)} \mathbf{h}_{k-1}, \quad W \in \mathbb{R}^{10 \times N_{k-1}}$$

$$\hat{y}_i = \frac{\exp(a_i^{(k)})}{\sum_j \exp(a_j^{(k)})}, \quad i = 1, \dots, 10$$

# Final layer with softmax activation

Last layer should generate a 10-dimensional vector with probability of each digit

$$\mathbf{a}^{(k)} = W^{(k)} \mathbf{h}_{k-1}, \quad W \in \mathbb{R}^{10 \times N_{k-1}}$$

$$\hat{y}_i = \operatorname{softmax}(\mathbf{a}^{(k)})_i, \quad i = 1, \dots, 10$$

# Final layer with softmax activation

Last layer should generate a 10-dimensional vector with probability of each digit

$$\mathbf{z} = W^{(k)} \mathbf{h}_{k-1}, \quad W \in \mathbb{R}^{10 \times N_{k-1}}$$
  
 $\hat{y}_i = \operatorname{softmax}(\mathbf{z})_i, \quad i = 1, \dots, 10$ 

### Categorical cross-entropy loss

Training example:

$$(\mathbf{x}, y)$$
  $y \in 1, \dots, 10$ 

Categorical cross-entropy loss:

$$\log p(y|\mathbf{x}; \theta) = \log \operatorname{softmax}(\mathbf{z})_y$$
$$= \mathbf{z}_y - \log \sum_{j=1}^{10} \exp(\mathbf{z}_j)$$

### Model training

Training example:

$$(\mathbf{x}, y)$$
  $y \in 1, \dots, 10$ 

Categorical cross-entropy loss:

$$\log p(y|\mathbf{x}; \theta) = \log \operatorname{softmax}(\mathbf{z})_y$$
$$= \mathbf{z}_y - \log \sum_{j=1}^{10} \exp(\mathbf{z}_j)$$

• For a training dataset  $\mathcal{D} = \{(\mathbf{x}_d, y_d)\}, \quad d = 1, \dots, N$ 

$$\mathcal{L}(\theta) = -\frac{1}{N} \sum_{d} \log p(y_d | \mathbf{x}_d; \theta)$$

# Take a quiz!