

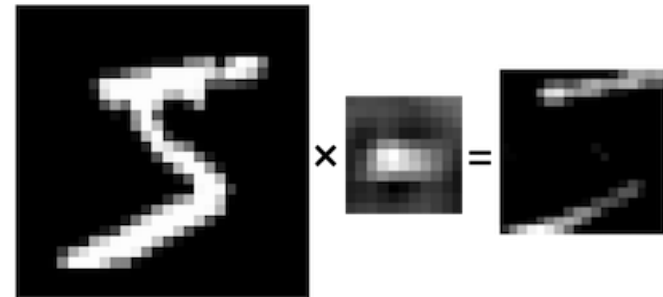
# Introduction to Deep Learning

## CNNs Part I

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# Schedule

- Recap (Kristin, Tunc)
- Loss functions (cross-entropy, MSE)
- Programming MLP & visualization
  - CNN Quiz

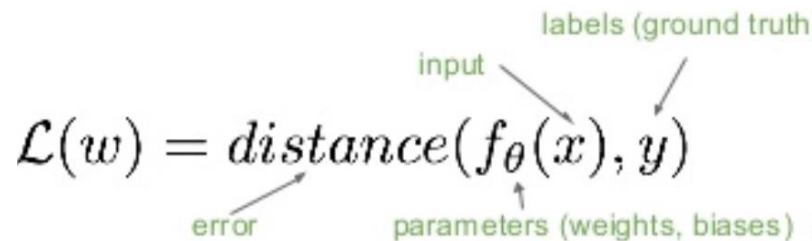
# Last time on IDL

MLPs, gradient descent, backprop

# Loss functions: Cross-entropy and MSE

# Loss functions

- measure the quality of network output values
- With respect to the difference between
  - output unit activations  $\leftrightarrow$  ground truth labels (targets)

$$\mathcal{L}(w) = \text{distance}(f_{\theta}(x), y)$$
A diagram explaining the components of the loss function equation. Arrows point from descriptive labels to parts of the equation: "input" points to  $x$ , "labels (ground truth)" points to  $y$ , "parameters (weights, biases)" points to  $\theta$ , and "error" points to the "distance" function.

input

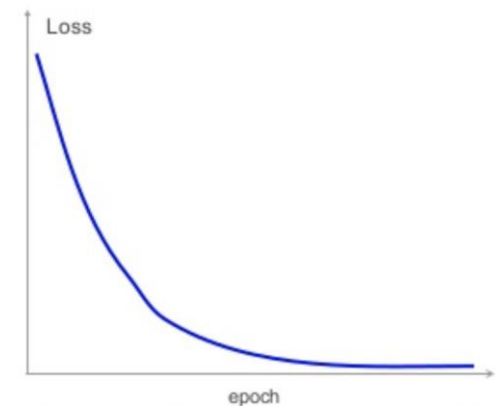
labels (ground truth)

error

parameters (weights, biases)

# Loss functions

- loss functions are used to guide the learnable parameters towards the desired performance
- by minimization of the loss function's value
- *average* loss is computed as the average of of each example (or *batch* loss)



$$\mathcal{L}(w) = \text{distance}(f_{\theta}(x), y)$$

Labels (ground truth)  $y$   
input  $x$   
parameters (weights, biases)  $\theta$   
error  $\mathcal{L}(w)$

# Types of loss functions

- Depending network and task type:
- Classification
  - categorical output
  - e.g. *cross-entropy loss*
- Regression
  - continuous, numeric output
  - e.g. *mean absolute error* (MAE, L1)
  - e.g. *mean squared error* (MSE, L2)

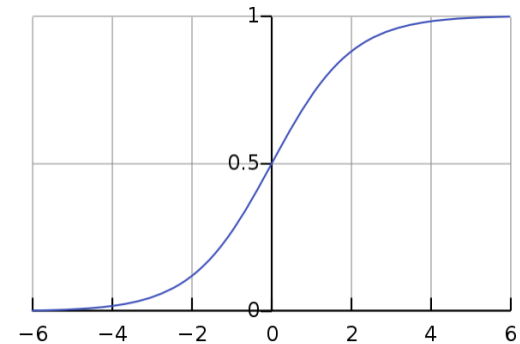
$$-\sum_{c=1}^M y_{o,c} \log(p_{o,c})$$

$$MAE = \frac{\sum_{i=1}^n |y_i - \hat{y}_i|}{n}$$

$$MSE = \frac{\sum_{i=1}^n (y_i - \hat{y}_i)^2}{n}$$

# Output activation functions

- transform output unit vector for loss computation (in training)
- transformed outputs are also used for prediction (after training)
- **Sigmoid** function
  - transforms a vector into range (0, 1)
  - applied independently to each element
- **Softmax** function
  - sum of categorical probabilities is 1
  - cross-entropy loss



$$f_j(z) = \frac{e^{z_j}}{\sum_k e^{z_k}}$$



# Mean Squared Error (MSE, L2)

$$MSE = \frac{\sum_{i=1}^n (y_i - \hat{y}_i)^2}{n}$$

- Sum of squared errors between predictions and ground truth
- squared error is always positive
- basic loss function for regression tasks (continuous, numeric variables)

# Cross-entropy







$$-(y \log(p) + (1 - y) \log(1 - p))$$

- categorical output: probability value between 0 and 1
  - multiplies the log of the predicted probability with the ground truth
  - when the ground truth is 0 ( $y(i) = 0$ ), then the first part is zero
  - when ground truth is 1 ( $y(i) = 1$ ), second part is zero
- penalizes strongly the predictions that are confident and wrong

# Cross-entropy

$$-\sum_{c=1}^M y_{o,c} \log(p_{o,c})$$

- Multiple classes  $\rightarrow$  sum of losses for each class label

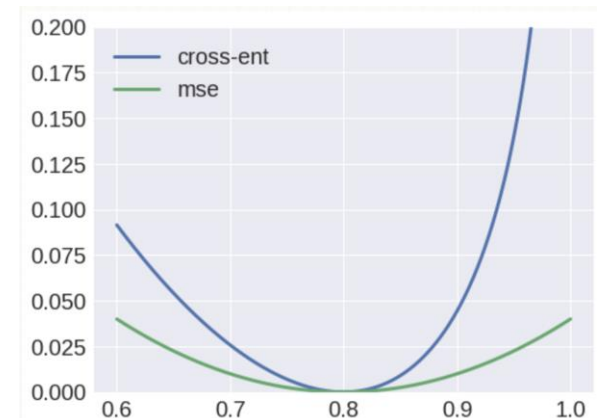
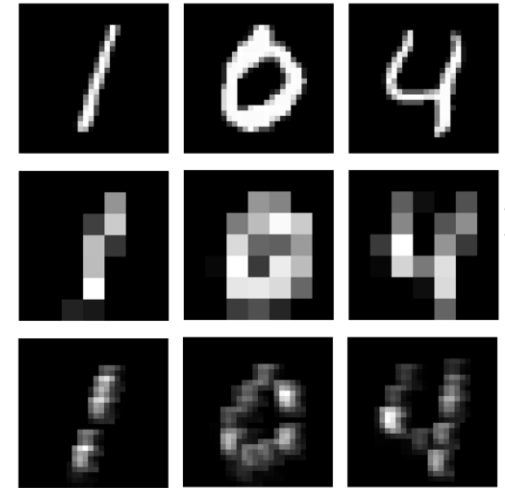
Multi-Class		Multi-Label	
C = 3	Samples	Samples	
	  	  	
	Labels (t) [0 0 1] [1 0 0] [0 1 0]	Labels (t) [1 0 1] [0 1 0] [1 1 1]	

[gombru.github.io/2018/05/23/cross\\_entropy\\_loss/](http://gombru.github.io/2018/05/23/cross_entropy_loss/)

# Cross-entropy or MSE?

Example: comparing image data

- applicable loss functions:
  - cross entropy (categorical, binary)
  - mean squared error
- important factors:
  - assumptions about data distribution
  - task / goal
  - activation function



# Programming MLP & visualization

Student demo & open discussion

# Convolution Quiz

in 5 groups

# Assignments until next week

- Reading:  
CNNs Part II
- Programming exercise:  
CNN for MNIST  
Filter visualization

Slides & assignments on:

[https://mlcogup.github.io/idl\\_ws18/](https://mlcogup.github.io/idl_ws18/)