

# Introduction to Deep Learning (I2DL)

## **Exercise 2: Math Recap**

# Overview

## Linear Algebra

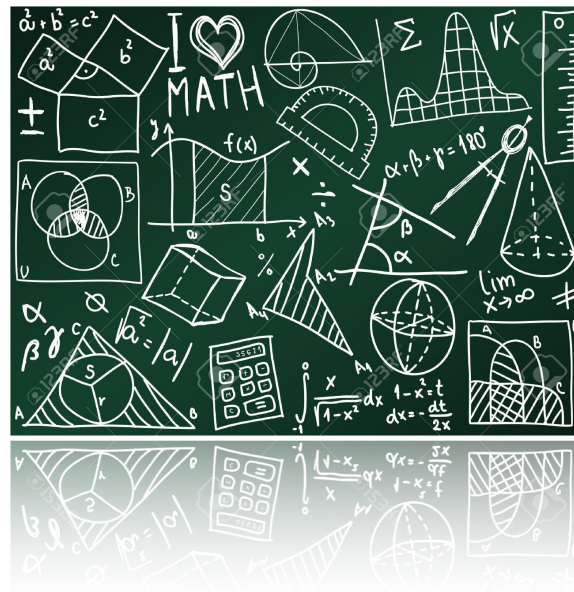
- Vectors and matrices
- Basic operations on matrices & vectors
- Tensors
- Norms, Loss functions

## Calculus

- Scalar derivatives
- Gradient
- Jacobian Matrix
- Chain Rule

## Probability Theory

- Probability space
- Random variables
- PMF, PDF, CDF
- Mean, variance
- Standard probability distributions



# Linear Algebra

# Overview

# Linear Algebra

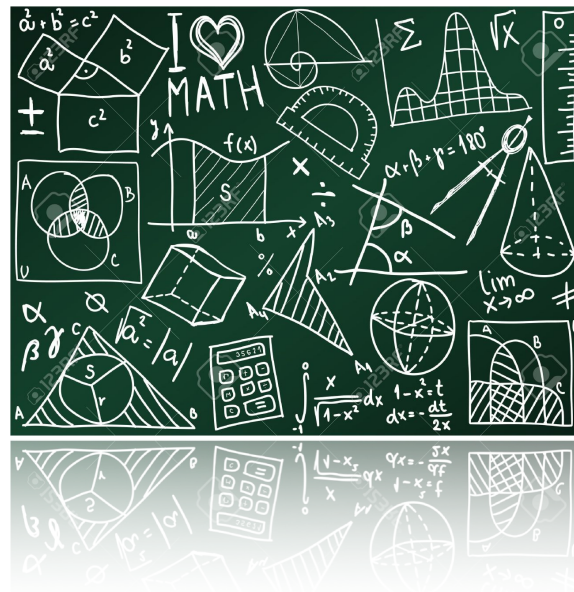
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# Basic Notation

- **Vector:** We call an element of  $\mathbb{R}^n$  a vector with  $n$  entries.
- **Elements of a vector:** The  $i$ th element of a vector  $\mathbf{v} \in \mathbb{R}^n$  is denoted by  $v_i \in \mathbb{R}$ .
- **Matrix:** We call an element of  $\mathbb{R}^{n \times m}$  a matrix with  $n$  rows and  $m$  columns.
- **Elements of a matrix:** For  $A \in \mathbb{R}^{n \times m}$ , we denote the element at the  $i$ th row and  $j$ th column by  $A_{ij} \in \mathbb{R}$ .
- **Transpose:** The transpose of a matrix results from “flipping” rows and columns. We denote the transpose of a matrix  $A \in \mathbb{R}^{n \times m}$  by  $A^T \in \mathbb{R}^{m \times n}$ . Similarly, we use transposed vectors.

# Vector

An n-dimensional vector describes an element in an n-dimensional space

$$\mathbf{v} = \begin{pmatrix} v_1 \\ v_2 \\ \vdots \\ v_n \end{pmatrix} \in \mathbb{R}^n$$



Vector  
Operations:

Addition

Subtraction

Scalar  
Multiplication

Dot Product

# Vector Operations

Vector  
Operations:

**Addition**

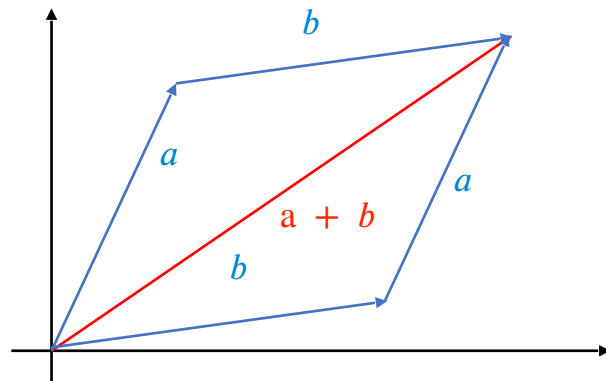
Subtraction

Scalar  
Multiplication

Dot Product

For  $a, b \in \mathbb{R}^n$  we have

$$a + b = \begin{pmatrix} a_1 + b_1 \\ a_2 + b_2 \\ \vdots \\ a_n + b_n \end{pmatrix} \in \mathbb{R}^n$$



# Vector Operations

Vector  
Operations:

Addition

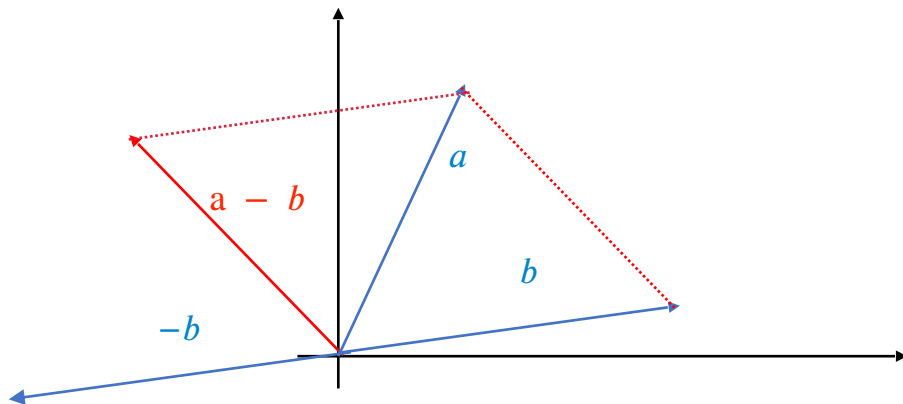
**Subtraction**

Scalar  
Multiplication

Dot Product

For  $a, b \in \mathbb{R}^n$  we have

$$a - b = \begin{pmatrix} a_1 - b_1 \\ a_2 - b_2 \\ \vdots \\ a_n - b_n \end{pmatrix} \in \mathbb{R}^n$$





# Vector Operations

Vector  
Operations:

Addition

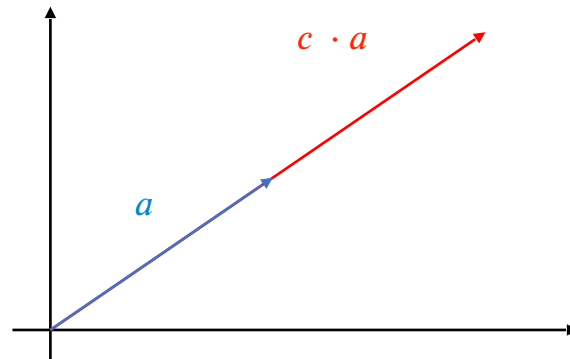
Subtraction

Scalar  
Multiplication

Dot Product

For  $a \in \mathbb{R}^n, c \in \mathbb{R}$  we have

$$c \cdot a = \begin{pmatrix} c \cdot a_1 \\ c \cdot a_2 \\ \vdots \\ c \cdot a_n \end{pmatrix} \in \mathbb{R}^n$$



# Vector Operations

Vector  
Operations:

Addition

Subtraction

Scalar  
Multiplication

**Dot Product**

**Definition:** For  $a, b \in \mathbb{R}^n$ , the dot product is defined as follows:

$$\begin{aligned} a \cdot b &= a^T \cdot b \\ &= a_1 \cdot b_1 + a_2 \cdot b_2 + \dots + a_n \cdot b_n \\ &= \sum_{i=1}^n a_i \cdot b_i \in \mathbb{R} \end{aligned}$$

# Vector Operations

Vector  
Operations:

Addition

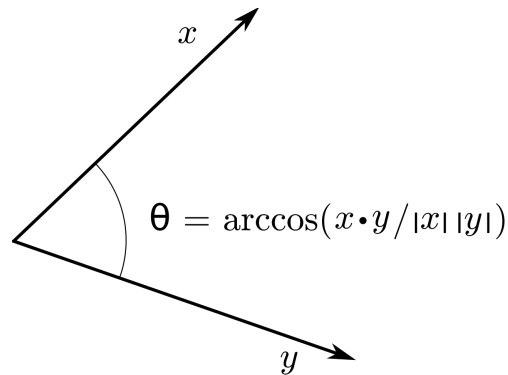
Subtraction

Scalar  
Multiplication

**Dot Product**

## Properties:

- Commutative:  $a \cdot b = b \cdot a$
- Geometric interpretation:  $a \cdot b = \|a\| \cdot \|b\| \cdot \cos(\theta)$
- Orthogonality: Two non-zero vectors are orthogonal to each other  $\iff a \cdot b = 0$



# Vector Operations

Vector  
Operations:

Addition

Subtraction

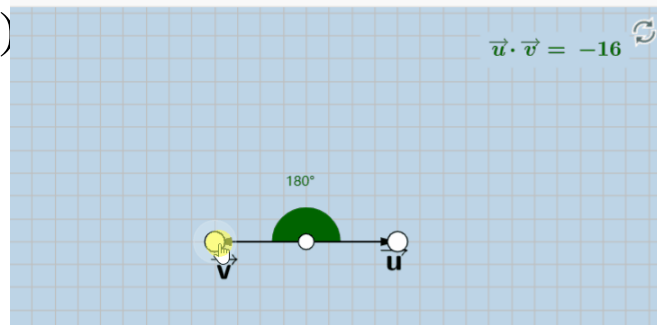
Scalar  
Multiplication

**Dot Product**

## Properties:

- Commutative:  $a \cdot b = b \cdot a$
- Geometric interpretation:  $a \cdot b = \|a\| \cdot \|b\| \cdot \cos(\theta)$
- Orthogonality: Two non-zero vectors are orthogonal to each other  $\iff a \cdot b = 0$

$$\vec{u} \cdot \vec{v} = \|\vec{u}\| \|\vec{v}\| \cos \theta = (4)(4) \cos 180^\circ = -16$$



# Matrix

A matrix  $\mathbf{A} \in \mathbb{R}^{n \times m}$  is denoted as

$$\mathbf{A} = \begin{pmatrix} a_{11} & a_{12} & \dots & a_{1m} \\ a_{21} & a_{22} & \dots & a_{2m} \\ \vdots & \vdots & \ddots & \vdots \\ a_{n1} & a_{n2} & \dots & a_{nm} \end{pmatrix} \in \mathbb{R}^{n \times m}$$

Matrix  
Operations:

Matrix-vector  
Multiplication

Matrix-matrix  
Multiplication

Hadamard  
Product

# Matrix

Matrix  
Operations:

Matrix-vector  
Multiplication

Matrix-matrix  
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Hadamard  
Product

- Multiplication of matrix with a vector is defined as follows:

$$\text{For } A \in \mathbb{R}^{n \times m}, b \in \mathbb{R}^m: A \cdot b = \begin{pmatrix} a_{11} & a_{12} & \dots & a_{1m} \\ a_{21} & a_{22} & \dots & a_{2m} \\ \vdots & \vdots & \ddots & \vdots \\ a_{n1} & a_{n2} & \dots & a_{nm} \end{pmatrix} \cdot \begin{pmatrix} b_1 \\ b_2 \\ \vdots \\ b_m \end{pmatrix} = \begin{pmatrix} a_{11} \cdot b_1 + a_{12} \cdot b_2 + \dots + a_{1m} \cdot b_m \\ a_{21} \cdot b_1 + a_{22} \cdot b_2 + \dots + a_{2m} \cdot b_m \\ \vdots \\ a_{n1} \cdot b_1 + a_{n2} \cdot b_2 + \dots + a_{nm} \cdot b_m \end{pmatrix} \in \mathbb{R}^n$$

- **Attention:** The respective dimension have to fit, otherwise the multiplication is not well-defined.

$$\implies \underbrace{A}_{n \times m} \cdot \underbrace{b}_{m \times 1} = \underbrace{c}_{n \times 1}$$

• **Example:**  $A \in \mathbb{R}^{3 \times 2}, b \in \mathbb{R}^2$  with  $A = \begin{pmatrix} 1 & 2 \\ 3 & 4 \\ 5 & 6 \end{pmatrix}$  and  $b = \begin{pmatrix} 2 \\ 3 \end{pmatrix} \implies \begin{pmatrix} 1 & 2 \\ 3 & 4 \\ 5 & 6 \end{pmatrix} \cdot \begin{pmatrix} 2 \\ 3 \end{pmatrix} = \begin{pmatrix} 8 \\ 18 \\ 28 \end{pmatrix}$

# Matrix Operations

Matrix  
Operations:

Matrix-vector  
Multiplication

Matrix-matrix  
Multiplication

Hadamard  
Product

- Similar, the multiplication of two matrices with each other is defined as follows:

For  $A \in \mathbb{R}^{n \times m}$ ,  $B \in \mathbb{R}^{m \times l}$  we have

$$A \cdot B = \begin{pmatrix} a_{11} & a_{12} & \dots & a_{1m} \\ a_{21} & a_{22} & \dots & a_{2m} \\ \vdots & \vdots & \ddots & \vdots \\ a_{n1} & a_{n2} & \dots & a_{nm} \end{pmatrix} \cdot \begin{pmatrix} b_{11} & b_{12} & \dots & b_{1l} \\ b_{21} & b_{22} & \dots & b_{2l} \\ \vdots & \vdots & \ddots & \vdots \\ b_{m1} & b_{m2} & \dots & b_{ml} \end{pmatrix} = \begin{pmatrix} c_{11} & c_{12} & \dots & c_{1l} \\ c_{21} & c_{22} & \dots & c_{2l} \\ \vdots & \vdots & \ddots & \vdots \\ c_{n1} & c_{n2} & \dots & c_{nl} \end{pmatrix} \in \mathbb{R}^{n \times l} \text{ where}$$

$$c_{ij} = \sum_{k=1}^m a_{ik} \cdot b_{kj} = a_{i1} \cdot b_{1j} + a_{i2} \cdot b_{2j} + \dots + a_{im} \cdot b_{mj}$$

- Attention: Matrix Multiplication is in general not commutative, i.e. for two matrices

$A \in \mathbb{R}^{n \times m}$ ,  $B \in \mathbb{R}^{m \times n}$  we have  $A \cdot B \neq B \cdot A$

# Matrix Operations

Matrix  
Operations:

Matrix-vector  
Multiplication

Matrix-matrix  
Multiplication

Hadamard  
Product

- The Hadamard product is the element wise product of two matrices. For two matrices of the same dimension  $A, B \in \mathbb{R}^{n \times m}$  it is given by

$$A \odot B = \begin{pmatrix} a_{11} & \dots & a_{1m} \\ a_{21} & \dots & a_{2m} \\ \vdots & \ddots & \vdots \\ a_{n1} & \dots & a_{nm} \end{pmatrix} \cdot \begin{pmatrix} b_{11} & \dots & b_{1m} \\ b_{21} & \dots & b_{2m} \\ \vdots & \ddots & \vdots \\ b_{n1} & \dots & b_{nm} \end{pmatrix} = \begin{pmatrix} a_{11} \cdot b_{11} & \dots & a_{1m} \cdot b_{1m} \\ a_{21} \cdot b_{21} & \dots & a_{2m} \cdot b_{2m} \\ \vdots & \ddots & \vdots \\ a_{n1} \cdot b_{n1} & \dots & a_{nm} \cdot b_{nm} \end{pmatrix} \in \mathbb{R}^{n \times m}$$

→ For all matrix operations, it is important to check the dimensions!

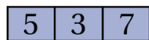


# Tensor

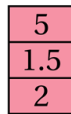
- Definition: A tensor is a multidimensional array and a generalization of the concepts of a vector and a matrix.

(11)

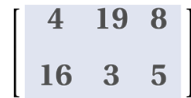
SCALAR



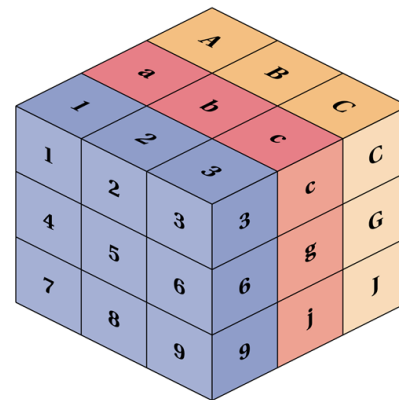
Row Vector  
(shape 1x3)



Column Vector  
(shape 3x1)



MATRIX



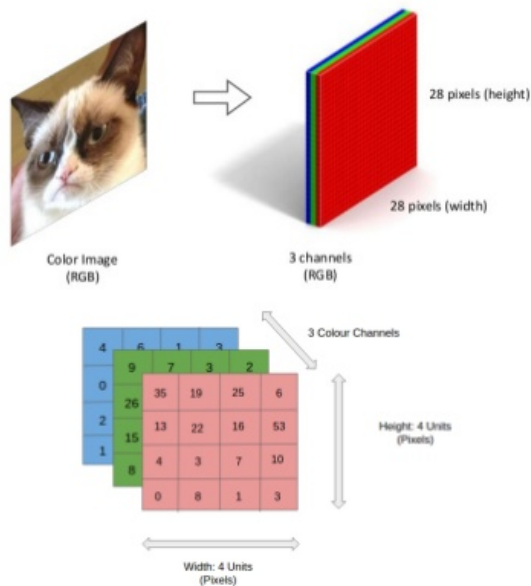
TENSOR

# Tensors in Computer Vision

color image is 3rd-order tensor

*Tensors are used to represent RGB images.*

$H \times W \times RGB$



Source: <https://www.slideshare.net/BertonEarnshaw/a-brief-survey-of-tensors>

# Norm

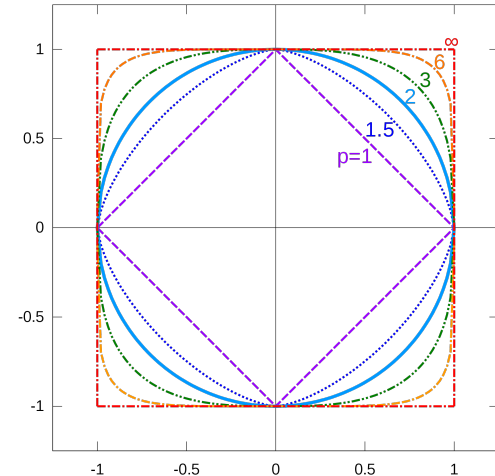
- **Norm:** measure of the “length” of a vector
- **Definition:** A norm is a non-negative function  $\| \cdot \| : V \rightarrow \mathbb{R}$  which is defined by the following the properties for elements  $v, w \in V$ :
  1. Triangle inequality:  $\|v + w\| \leq \|v\| + \|w\|$
  2.  $\|a \cdot v\| = |a| \cdot \|v\|$  for a scalar  $a$
  3.  $\|v\| = 0$  if and only if  $v = 0$(\* $V$  is a vector space over a field  $\mathbb{F}$ ; in our case we have  $V = \mathbb{R}^n$ )
- **Remark:** Every such function defines a norm on the vector space.
- **Examples:** L1-norm, L2-norm

# L1-Norm

- **Norm:** measure of the “length” of a vector
- **L1-Norm:** We denote the L1-norm with  $\| \cdot \|_1 : \mathbb{R}^n \rightarrow \mathbb{R}$  such that for a vector  $v = (v_1, v_2, \dots, v_n)$

$$\|v\|_1 = \sum_{i=1}^n |v_i|$$

- **Example:** Let  $v = \begin{pmatrix} 1 \\ -3 \\ 2 \end{pmatrix} \in \mathbb{R}^3$ , then  
 $\|v\|_1 = (1 + 3 + 2) = 6$



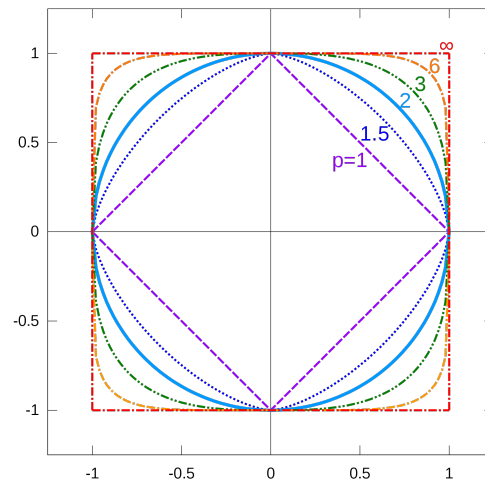
# L2-Norm

- **Norm:** measure of the “length” of a vector
- **L2-Norm:** We denote the L2-norm with  $\| \cdot \|_2 : \mathbb{R}^n \rightarrow \mathbb{R}$  such that for a vector  $v = (v_1, v_2, \dots, v_n)$

$$\|v\|_2 = \sqrt{\sum_{i=1}^n (v_i)^2}$$

- **Example:** Let  $v = \begin{pmatrix} 1 \\ -3 \\ 2 \end{pmatrix} \in \mathbb{R}^3$ , then

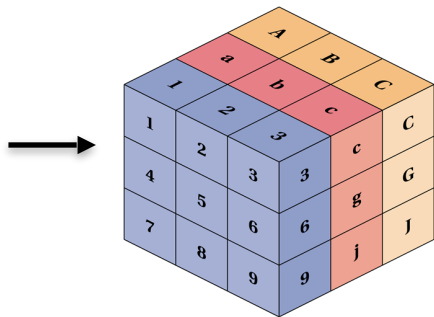
$$\|v\|_2 = \sqrt{(1^2 + (-3)^2 + 2^2)} = \sqrt{14}$$



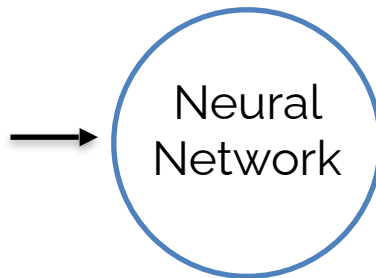
# Loss functions

- A loss function is a function that takes as input two vectors and as output measures the distance between these two
  - uses a norm to measure the distance
  - L1-Loss uses the L1-norm, L2-Loss uses the L2-norm
- **L1-Loss:** The L1-Loss between two vectors  $\mathbf{v}, \mathbf{w} \in \mathbb{R}^n$  is defined as  $L_1(\mathbf{v}, \mathbf{w}) = \|\mathbf{v} - \mathbf{w}\|_1 = (v_1 - w_1) + \dots + (v_n - w_n)$
- **L2-Loss:** The L2-Loss between two vectors  $\mathbf{v}, \mathbf{w} \in \mathbb{R}^n$  is defined as  $L_2(\mathbf{v}, \mathbf{w}) = \|\mathbf{v} - \mathbf{w}\|_2 = \sqrt{(v_1 - w_1)^2 + \dots + (v_n - w_n)^2}$

# Outlook



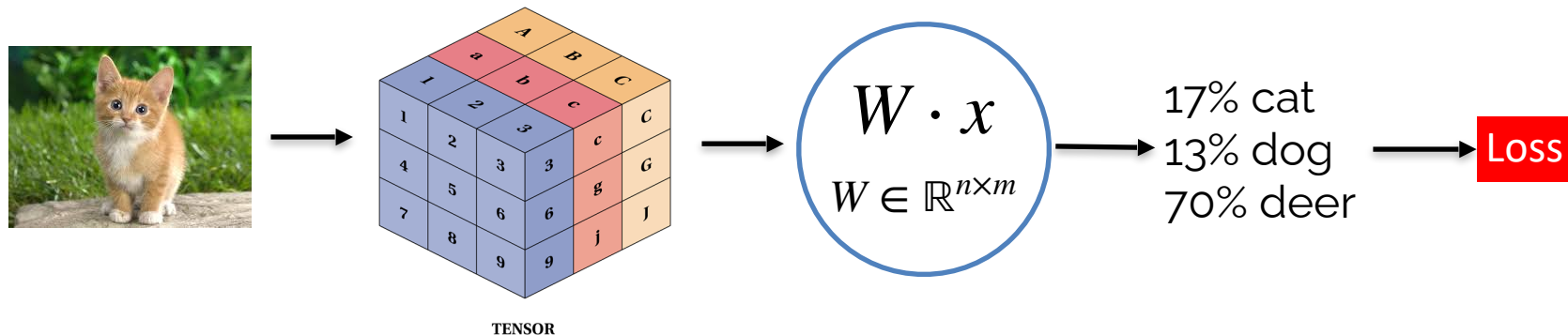
TENSOR



17% cat  
13% dog  
70% deer

Loss

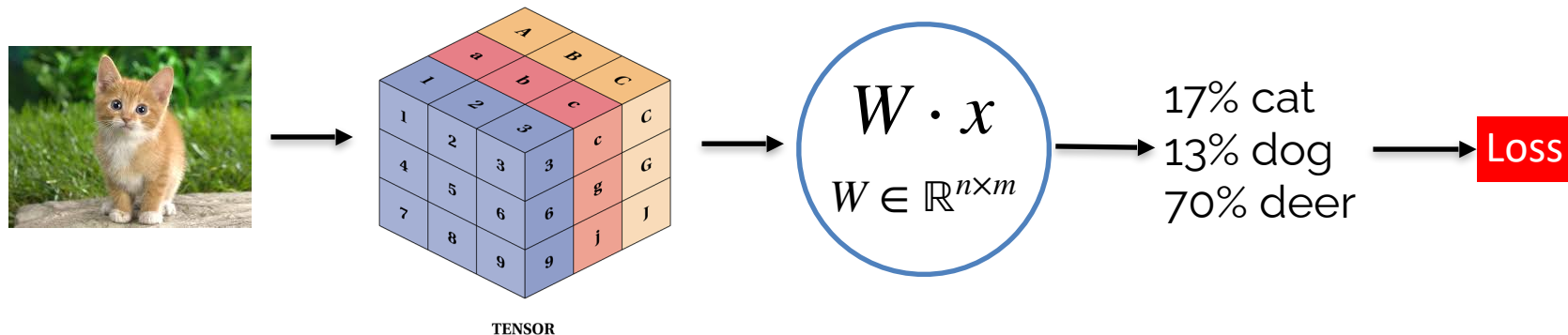
# Outlook



*The elements of the matrix  $W$  are called weights and they determine the prediction of our network.*

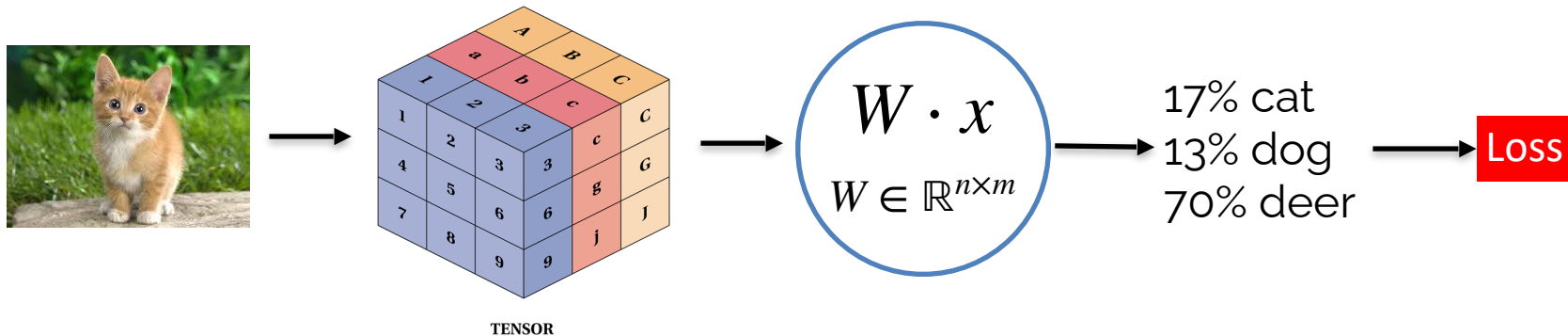


# Outlook



*How can we get an accurate matrix  $W$  to minimize the loss?*

# Outlook



*Gradient Descent: Method to approximate the best values for the weights*

# Calculus

# Overview

## Linear Algebra

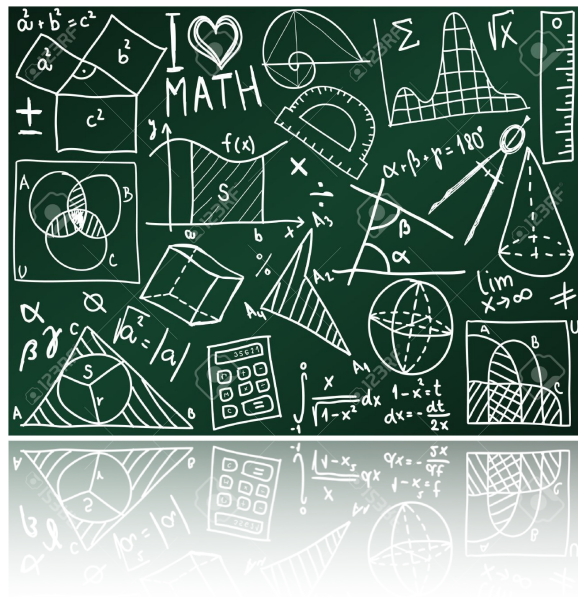
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# Derivatives

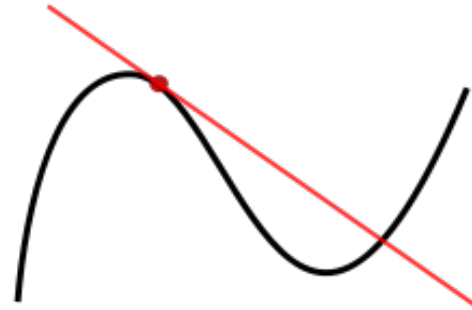
- **Well known:** Scalar derivatives, i.e. derivatives of functions  $f: \mathbb{R} \rightarrow \mathbb{R}$
- **Matrix calculus:** Extension of calculus to higher dimensional setting, i.e. functions like  $f: \mathbb{R}^n \rightarrow \mathbb{R}$ ,  $f: \mathbb{R} \rightarrow \mathbb{R}^n$ ,  $f: \mathbb{R}^n \rightarrow \mathbb{R}^m$  and  $f: \mathbb{R}^{n \times m} \rightarrow \mathbb{R}$  for  $n, m \in \mathbb{N}$
- Actual calculus we use is relatively trivial, but the notation can often make things look much more difficult than they are.

# Overview

Setting	Derivative	Notation
$f : \mathbb{R} \rightarrow \mathbb{R}$	Scalar derivative	$f'(x)$
$f : \mathbb{R}^n \rightarrow \mathbb{R}$	Gradient	$\nabla f(x)$
$f : \mathbb{R}^{n \times m} \rightarrow \mathbb{R}$	Gradient	$\nabla f(x)$
$f : \mathbb{R}^n \rightarrow \mathbb{R}^m$	Jacobian	$J_f$

# Scalar derivatives

- **Setting:**  $f : \mathbb{R} \rightarrow \mathbb{R}$
- **Notation:**  $f'(x)$  or  $\frac{df}{dx}$
- **Derivative:** Derivative of a function at a chosen input value is the slope of the tangent line to the graph of the function at that point.



# Derivation Rules

Common functions	Derivative
$f(x) = c$ for $c \in \mathbb{R}$	$f'(x) = 0$
$f(x) = x$	$f'(x) = 1$
$f(x) = x^n$ for $n \in \mathbb{N}$	$f'(x) = n \cdot x^{n-1}$
$f(x) = e^x$	$f'(x) = e^x$
$f(x) = \ln(x)$	$f'(x) = \frac{1}{x}$
$f(x) = \sin(x)$	$f'(x) = \cos(x)$
$f(x) = \cos(x)$	$f'(x) = -\sin(x)$



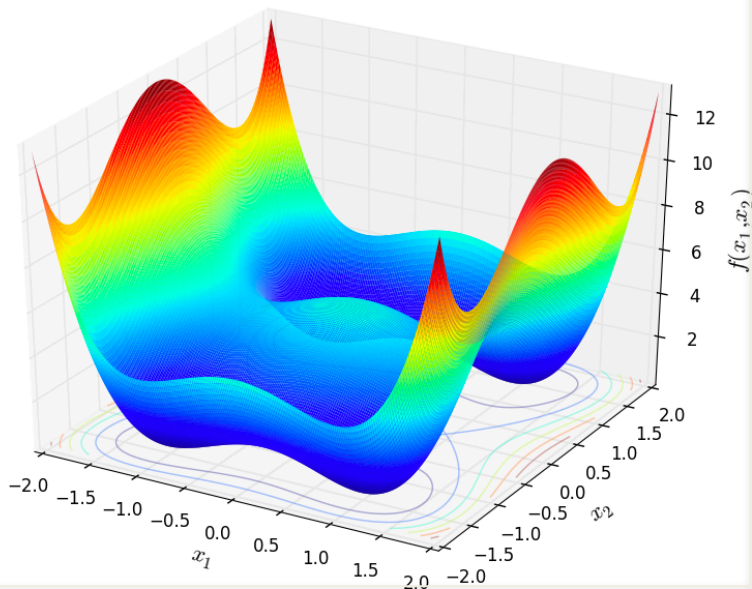
# Derivation Rules

Rule	Function	Derivative
Sum rule	$f(x) + g(x)$	$f'(x) + g'(x)$
Difference rule	$f(x) - g(x)$	$f'(x) - g'(x)$
Multiplication by constant	$c \cdot f(x)$	$c \cdot f'(x)$
Product rule	$f(x) \cdot g(x)$	$f'(x) \cdot g(x) + f(x) \cdot g'(x)$
Quotient rule	$\frac{f(x)}{g(x)}$	$\frac{f'(x) \cdot g(x) - f(x) \cdot g'(x)}{(g(x))^2}$
Chain rule	$f(g(x))$	$f'(g(x)) \cdot g'(x)$

# Multivariate functions $f : \mathbb{R}^n \rightarrow \mathbb{R}$

## Multivariate Function

$$f : \mathbb{R}^n \rightarrow \mathbb{R}$$



## Gradient

$$\nabla f : \mathbb{R}^n \rightarrow \mathbb{R}^n$$

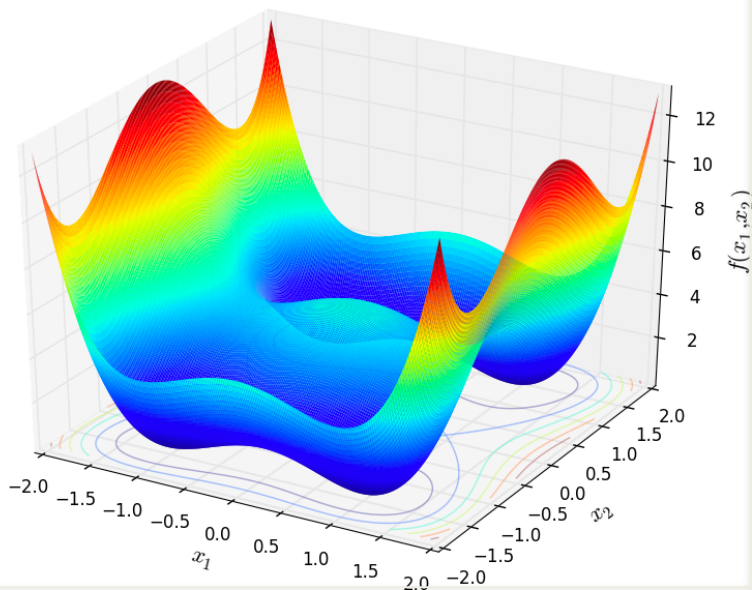
Partial derivative

$$\nabla f : x \rightarrow \nabla f(x) = \begin{pmatrix} \frac{\partial f(x)}{\partial x_1} \\ \frac{\partial f(x)}{\partial x_2} \\ \vdots \\ \frac{\partial f(x)}{\partial x_n} \end{pmatrix}$$

# Multivariate functions $f : \mathbb{R}^{n \times m} \rightarrow \mathbb{R}$

## Multivariate Function

$$f : \mathbb{R}^{n \times m} \rightarrow \mathbb{R}$$

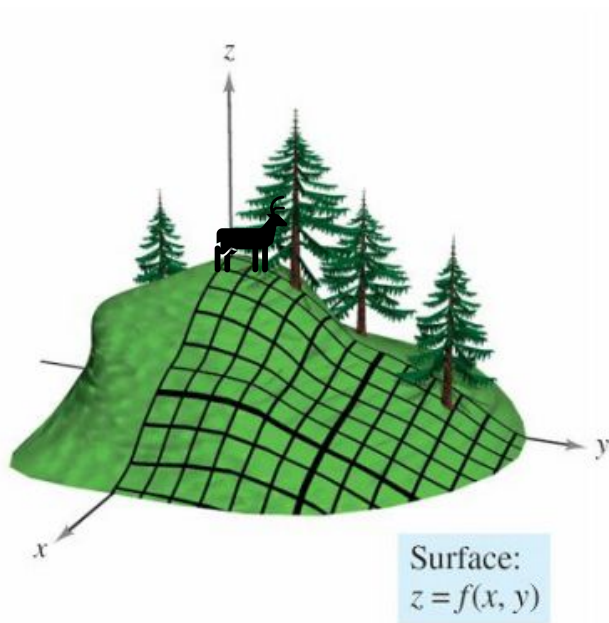


## Gradient

$$\nabla f : \mathbb{R}^{n \times m} \rightarrow \mathbb{R}^{n \times m}$$

$$\nabla f : x \rightarrow \nabla f(x) = \begin{pmatrix} \frac{\partial f(x)}{\partial x_{11}} & \frac{\partial f(x)}{\partial x_{12}} & \cdots & \frac{\partial f(x)}{\partial x_{1m}} \\ \frac{\partial f(x)}{\partial x_{21}} & \frac{\partial f(x)}{\partial x_{22}} & \cdots & \frac{\partial f(x)}{\partial x_{2m}} \\ \vdots & \vdots & \ddots & \vdots \\ \frac{\partial f(x)}{\partial x_{n1}} & \frac{\partial f(x)}{\partial x_{n2}} & \cdots & \frac{\partial f(x)}{\partial x_{nm}} \end{pmatrix}$$

# Gradient – Example 1



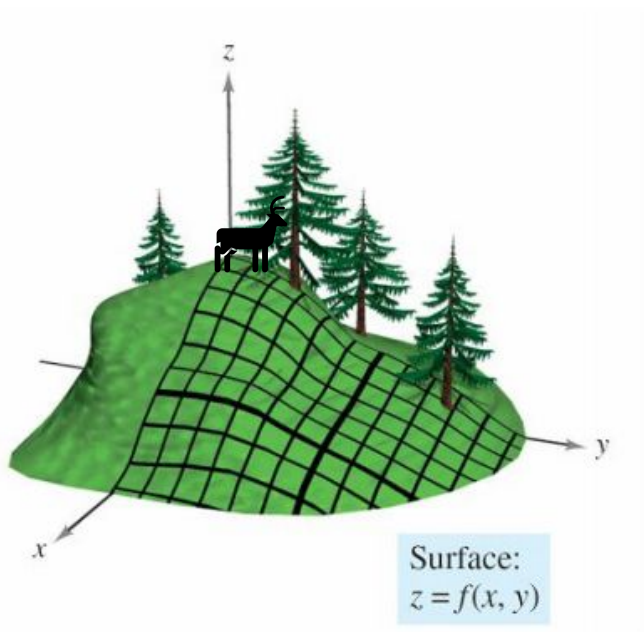
$$f(x, y) = 3x^2y \quad \nabla f(x, y) = \left[ \frac{\partial f(x, y)}{\partial x}, \frac{\partial f(x, y)}{\partial y} \right]$$

$$\frac{\partial}{\partial x} 3yx^2 = 3y \frac{\partial}{\partial x} x^2 = 3y 2x = 6yx$$

$$\frac{\partial}{\partial y} 3x^2y = 3x^2 \frac{\partial}{\partial y} y = 3x^2 \frac{\partial y}{\partial y} = 3x^2 \times 1 = 3x^2$$

$$\nabla f(x, y) = \left[ \frac{\partial f(x, y)}{\partial x}, \frac{\partial f(x, y)}{\partial y} \right] = [6yx, 3x^2]$$

# Gradient – Example 2



$$g(x, y) = 2x + y^8$$

$$\frac{\partial g(x, y)}{\partial x} = \frac{\partial 2x}{\partial x} + \frac{\partial y^8}{\partial x} = 2 \frac{\partial x}{\partial x} + 0 = 2 \times 1 = 2$$

$$\frac{\partial g(x, y)}{\partial y} = \frac{\partial 2x}{\partial y} + \frac{\partial y^8}{\partial y} = 0 + 8y^7 = 8y^7$$

$$\nabla g(x, y) = [2, 8y^7]$$

# Vector-valued functions

## Vector-Valued function

$$f : \mathbb{R}^n \rightarrow \mathbb{R}^m$$

$$f : x = \begin{pmatrix} x_1 \\ x_2 \\ \vdots \\ x_n \end{pmatrix} \longrightarrow \begin{pmatrix} f_1(x) \\ f_2(x) \\ \vdots \\ f_m(x) \end{pmatrix}$$

## Jacobian Matrix

$$J_f : \mathbb{R}^n \rightarrow \mathbb{R}^{m \times n}$$

$$x \rightarrow J_f(x) = \begin{pmatrix} \frac{\partial f_1(x)}{\partial x_1} & \frac{\partial f_1(x)}{\partial x_2} & \cdots & \frac{\partial f_1(x)}{\partial x_n} \\ \frac{\partial f_2(x)}{\partial x_1} & \frac{\partial f_2(x)}{\partial x_2} & \cdots & \frac{\partial f_2(x)}{\partial x_n} \\ \vdots & \vdots & \ddots & \vdots \\ \frac{\partial f_m(x)}{\partial x_1} & \frac{\partial f_m(x)}{\partial x_2} & \cdots & \frac{\partial f_m(x)}{\partial x_n} \end{pmatrix}$$

# Jacobian Matrix – Example 3

Assume that  $f : \mathbb{R}^2 \rightarrow \mathbb{R}^2$  with  $f(x, y) = \begin{pmatrix} f_1(x, y) \\ f_2(x, y) \end{pmatrix}$  where  
 $f_1(x, y) = 3x^2y$  and  $f_2(x, y) = 2x + y^8$ .

Calculate Jacobian matrix:

$$J_f(x) = \begin{pmatrix} \frac{\partial f_1(x, y)}{\partial x} & \frac{\partial f_1(x, y)}{\partial y} \\ \frac{\partial f_2(x, y)}{\partial x} & \frac{\partial f_2(x, y)}{\partial y} \end{pmatrix} = \begin{pmatrix} 6xy & 3x^2 \\ 2 & 8y^7 \end{pmatrix}$$

# Single Variable Chain Rule

**Setting:** We are given the function  $h(x) = f(g(x))$ .

**Task:** Compute the derivative of this function with chain rule.

1. **Introduce the intermediate variable:** Let  $u = g(x)$  be the intermediate variable.

2. **Compute individual derivatives:**  $\frac{df}{du}$  and  $\frac{dg}{dx} = \frac{du}{dx}$

3. **Chain rule:**  $\frac{dh}{dx} = \frac{df}{du} \cdot \frac{du}{dx}$

4. **Substitute intermediate variables back**



# Single Variable Chain Rule: Example

**Example:** Let  $h(x) = \sin(x^2)$ .

**Task:** Compute the derivative of this function with chain rule.

**Observation:** Here,  $h(x) = f(g(x))$  with  $f(x) = \sin(x)$  and  $g(x) = x^2$ .

1. **Introduce the intermediate variable:** Let  $u = x^2$  be the intermediate variable.

2. **Compute individual derivatives:**  $\frac{df}{du} = \cos(u)$  and  $\frac{dg}{dx} = \frac{du}{dx} = 2x$

3. **Chain rule:**  $\frac{dh}{dx} = \frac{df}{du} \cdot \frac{du}{dx} = \cos(u) \cdot 2x$

4. **Substitute intermediate variables back:**  $\frac{dh}{dx} = \cos(u) \cdot 2x = \cos(x^2) \cdot 2x$

# Total Derivative Chain Rule

General Formalism:

$$\begin{aligned}\frac{\partial f(x, u_1(x), \dots, u_n(x))}{\partial x} &= \frac{\partial f}{\partial x} + \frac{\partial f}{\partial u_1} \frac{\partial u_1}{\partial x} + \frac{\partial f}{\partial u_2} \frac{\partial u_2}{\partial x} + \dots + \frac{\partial f}{\partial u_n} \frac{\partial u_n}{\partial x} \\ &= \frac{\partial f}{\partial x} + \sum_{i=1}^n \frac{\partial f}{\partial u_i} \frac{\partial u_i}{\partial x}\end{aligned}$$

# References

- [https://en.wikipedia.org/wiki/Matrix\\_calculus](https://en.wikipedia.org/wiki/Matrix_calculus)
- <http://parrt.cs.usfca.edu/doc/matrix-calculus/index.html>
- <https://arxiv.org/pdf/1802.01528.pdf>
- <https://www.khanacademy.org/math/multivariable-calculus/multivariable-derivatives>
- <https://explained.ai/matrix-calculus/>
- [http://www.deeplearningbook.org/contents/part\\_basics.html](http://www.deeplearningbook.org/contents/part_basics.html)
- <https://towardsdatascience.com/calculating-gradient-descent-manually-6d9bee09aa0b>

# Probability Theory

# Overview

## Linear Algebra

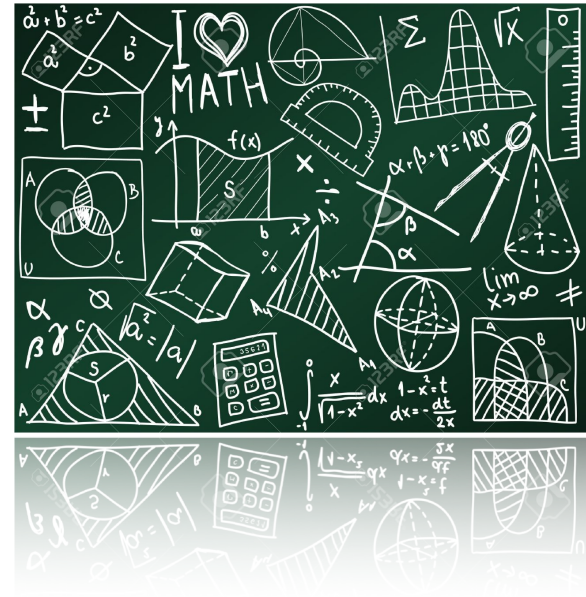
- Vectors and matrices
- Basic operations on matrices & vectors
- Tensors
- Norm & Loss functions

## Calculus

- Scalar derivatives
- Gradient
- Jacobian Matrix
- Chain Rule

## Probability Theory

- Probability space
- Random variables
- PMF, PDF, CDF
- Mean, variance
- Standard probability distributions



# Probability space $(\Omega, \mathcal{F}, \mathbb{P})$

A probability space consist of three elements  $(\Omega, \mathcal{F}, \mathbb{P})$ :

- **Sample space  $\Omega$ :** The set of all outcomes of a random experiment.
- **Event Space  $\mathcal{F}$ :** A set whose elements  $A \in \mathcal{F}$  (called events) are subsets of  $\Omega$ .
- **Probability measure  $\mathbb{P}$ :** A function  $\mathbb{P} : \mathcal{F} \rightarrow \mathbb{R}$  that satisfies the following three properties:
  1.  $\mathbb{P}(A) \geq 0$  for all  $A \in \mathcal{F}$
  2.  $\mathbb{P}(\Omega) = 1$
  3.  $\mathbb{P}\left(\bigcup_{i=1}^n A_i\right) = \sum_{i=1}^n \mathbb{P}(A_i)$  for  $n \in \mathbb{N}$  and disjoint events  $A_1, A_2, \dots, A_n \in \mathcal{F}$

→ *The probability space provides a formal model of a random experiment.*

# Probability space: Example

A probability space consists of three elements:  $(\Omega, \mathcal{F}, \mathbb{P})$

- **Sample space  $\Omega$ :** The set of all outcomes of a random experiment.
- **Event Space  $\mathcal{F}$ :** A set whose elements  $A \in \mathcal{F}$  (called events) are subsets of  $\Omega$ .
- **Probability measure  $\mathbb{P}$ :** A function  $\mathbb{P} : \mathcal{F} \rightarrow \mathbb{R}$  that satisfies the following three properties: (...)

## *Example: Tossing a six-sided die*

- **Sample space:**  $\Omega = \{1,2,3,4,5,6\}$
- **Event space:**  $\mathcal{F}_1 = \{\emptyset, \Omega\}$ ,  $\mathcal{F}_2 = \mathcal{P}(\Omega)$ ,  $\mathcal{F}_3 = \{\emptyset, A_1 = \{1,3,5\}, A_2 = \{2,4,6\}, \Omega = \{1,2,3,4,5,6\}\}$
- **Probability measure  $\mathbb{P} : \mathcal{F} \rightarrow \mathbb{R}$**  with  $\mathbb{P}(\emptyset) = 0$ ,  $\mathbb{P}(\Omega) = 1$  and in the case of  $\mathcal{F}_3$  we know that  $\mathbb{P}(A_1) + \mathbb{P}(A_2) = 1$ .
- **Example event space  $\mathcal{F}_3$  :** Possible probability measure are
  1.  $\mathbb{P}_1(A_1) = \frac{1}{2} = \mathbb{P}_1(A_2)$
  2.  $\mathbb{P}_2(A_1) = \frac{1}{4}$  and  $\mathbb{P}_2(A_2) = \frac{3}{4}$ .



# Random variable

- A random variable is a function defined on the probability space which maps from the sample space to the real numbers, i.e.

$$X : \Omega \rightarrow \mathbb{R}.$$

- We distinguish between **discrete** and **continuous** random variables.



# Random variable

- A random variable is a function defined on the probability space which maps from the sample space to the real numbers, i.e.  $X : \Omega \rightarrow \mathbb{R}$ .



## ***Example: Tossing a fair six-sided die***

- Underlying experiment:**  $\Omega = \{1,2,3,4,5,6\}$ ,  $\mathcal{F} = \mathcal{P}(\Omega)$ ,  $\mathbb{P}(\{x\}) = \frac{1}{6} \forall x \in \Omega$
- Random variable  $X$ :** Number that appears on the die,  $X : \Omega \rightarrow \{1,2,3,4,5,6\} \implies$  discrete random variable
- Example:** One element in  $\Omega$  is  $\omega = 4$ . Then  $X(\omega) = 4$ .
- Probability measure  $\mathbb{P}$ :**  
$$\mathbb{P}(X = 4) = \mathbb{P}(\{\omega \in \Omega : X(\omega) = \omega = 4\}) = \mathbb{P}(\{4\}) = \frac{1}{6}$$

discrete

# Random variable

- A random variable is a function defined on the probability space which maps from the sample space to the real numbers, i.e.  $X : \Omega \rightarrow \mathbb{R}$ .

## *Example: Flipping a fair coin two times*

- Underlying experiment:**  $\Omega = \{(H, H), (H, T), (T, H), (T, T)\}$ ,  
 $\mathcal{F} = \mathcal{P}(\Omega)$  and  $\mathbb{P}(\{\omega\}) = \frac{1}{4} \forall \omega \in \Omega$
- Random variable  $X$ :** number of heads that appeared in the two flips,  $X : \Omega \rightarrow \{0, 1, 2\} \implies$  discrete random variable
- Example:** One element in  $\Omega$  is  $\omega = (T, H)$ . Then  $X(\omega) = 1$ .
- Probability measure  $\mathbb{P}$ :**  
$$\mathbb{P}(X = 1) = \mathbb{P}(\{\omega \in \Omega : X(\omega) = 1\}) = \mathbb{P}(\{(H, T), (T, H)\}) = \frac{1}{2}$$



discrete

# Random variable

- A random variable is a function defined on the probability space which maps from the sample space to the real numbers, i.e.  $X : \Omega \rightarrow \mathbb{R}$ .

## ***Example: radioactive decay***

- **Underlying experiment:**  $\Omega = \mathbb{R}_{\geq 0}$ ,  $\mathcal{F} = \mathcal{B}(\Omega)$ ,  $\mathbb{P} = \lambda$  is the Lebesgue measure
- **Random variable  $X$ :** indicating amount of time that it takes for a radioactive particle to decay,  $X : \mathbb{R}_{\geq 0} \rightarrow \mathbb{R}_{\geq 0} \implies$  continuous random variable
- **Probability measure  $\mathbb{P}$ :** is defined on the set of events  $\mathcal{F}$  and is now used for random variables as follows:  
$$\mathbb{P}(a \leq X \leq b) = \mathbb{P}(\{\omega \in \Omega : a \leq X(\omega) \leq b\})$$



Continuous

# Probability measures

⇒ specify the probability measures with alternative functions (CDF, PDF and PMF)

Random Variable		
Discrete	Cumulative density function (CDF) $F_X(x) = \mathbb{P}(X \leq x)$	Probability mass function (PMF) $p_X(x) = \mathbb{P}(X = x)$
Continuous	Cumulative density function (CDF) $F_X(x) = \mathbb{P}(X \leq x)$	Probability density function (PDF)

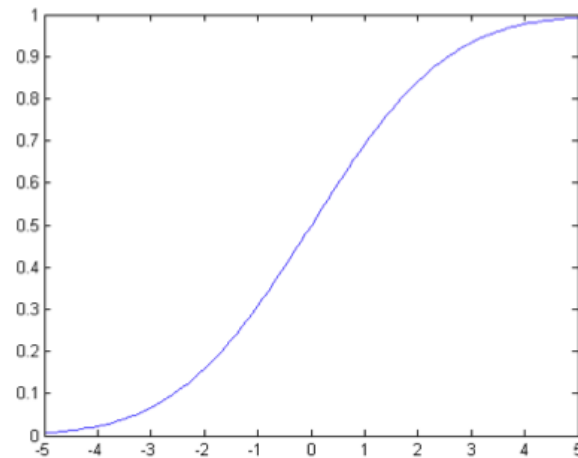
# Cumulative Distribution Function

- A **cumulative distribution function** (CDF) of a random variable  $\mathbf{X}$  is a function  $F_X : \mathbb{R} \rightarrow [0,1]$  which is defined as

$$F_X(x) = \mathbb{P}(X \leq x)$$

- **Properties:** Per definition, it satisfies the following properties:

1.  $0 \leq F_X(x) \leq 1$
2.  $\lim_{x \rightarrow -\infty} F_X(x) = 0$
3.  $\lim_{x \rightarrow \infty} F_X(x) = 1$
4.  $\forall x \leq y \implies F_X(x) \leq F_X(y)$



A sample CMF

# Discrete Case: Probability Mass Function

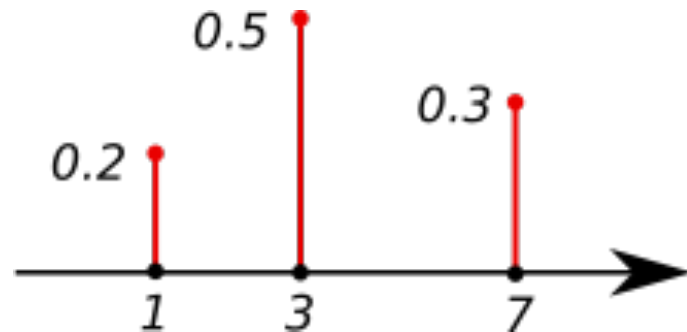
- The **probability mass function** of a random variable is a function  $p_X : \Omega \rightarrow \mathbb{R}$  defined as

$$p_X(x) = \mathbb{P}(X = x)$$

- Properties:** Again, we can derive some properties:

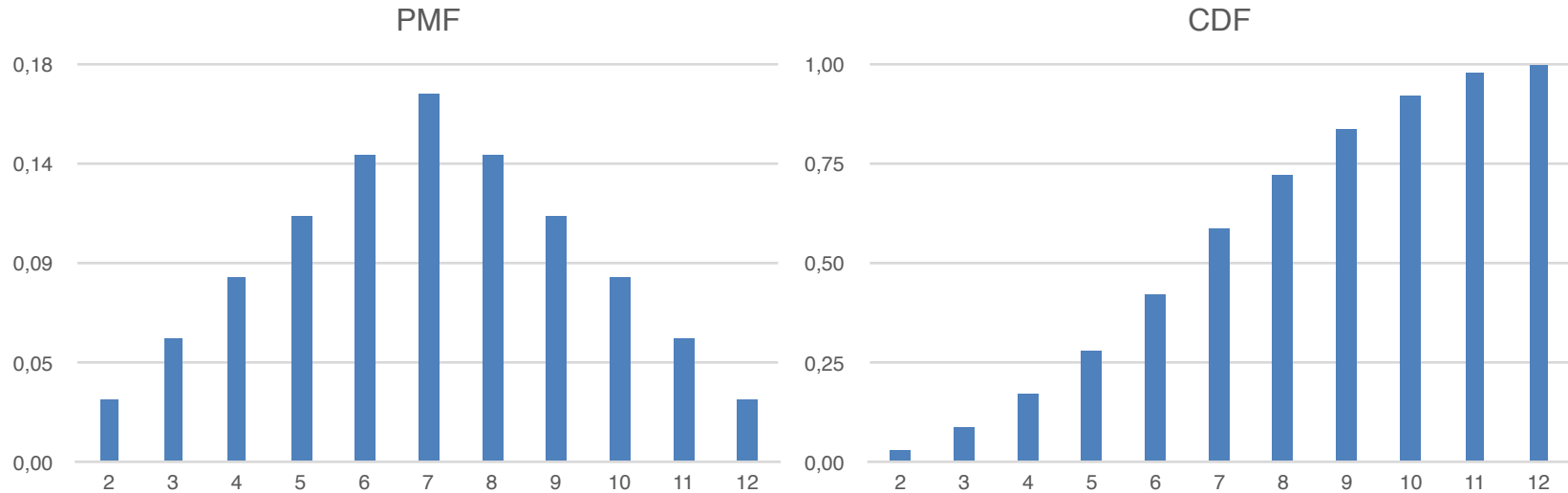
$$1. 0 \leq p_X(x) \leq 1$$

$$2. \sum_{x \in \Omega} p_X(x) = 1$$



A sample PMF

# Discrete Example: Sum of 2 Dice Rolls



# Continuous case: Probability Density Function

- **Continuous case:** For some continuous random variables, the CDF  $F_X(x)$  is differentiable everywhere. Then we define the probability density function as the function  $f_X(x) : \Omega \rightarrow \mathbb{R}$  with

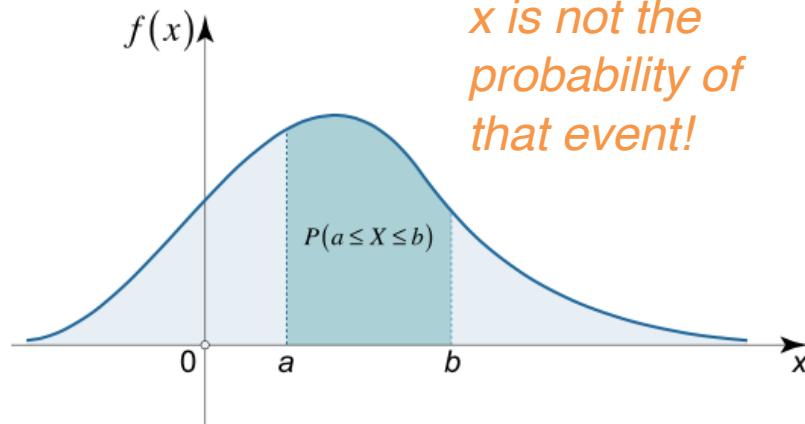
$$f_X(x) = \frac{dF_X(x)}{dx}$$

- **Properties:**

1.  $f_X(x) \geq 0$

2.  $\int_{-\infty}^{\infty} f_X(x) dx = 1$

3.  $\int_a^b f_X(x) dx = F_X(b) - F_X(a)$



*Note: the value of a PDF at any given point  $x$  is not the probability of that event!*



# Expectation of a random variable

- **Idea:** “weighted average” of the values that the random variable can take on
- **Discrete setting:** Assume that  $\mathbf{X}$  is a discrete random variable with PMF  $p_{\mathbf{X}}(x)$ . Then the expectation of  $\mathbf{X}$  is given by

$$\mathbb{E}[\mathbf{X}] = \sum_{x \in \Omega} x \cdot p_{\mathbf{X}}(x)$$

- **Continuous setting:** Assume that  $\mathbf{X}$  is a continuous random variable with PDF  $f_{\mathbf{X}}(x)$ . Then the expectation of  $\mathbf{X}$  is given by

$$\mathbb{E}[\mathbf{X}] = \int_{-\infty}^{\infty} x \cdot f_{\mathbf{X}}(x) \, dx$$

# Expectation: Example

- **Discrete setting:** Assume that  $X$  is a discrete random variable with PMF  $p_X(x)$ . Then the expectation of  $X$  is given by

$$\mathbb{E}[X] = \sum_{x \in \Omega} x \cdot p_X(x)$$



## Example: Tossing a six-sided die

$$\Omega = \{1, 2, 3, 4, 5, 6\}$$

$X$ : represents the outcome of the toss

$$p_X(x) = \mathbb{P}(X = x) = \frac{1}{6} \quad \forall x \in \Omega$$

$$\mathbb{E}[X] = \sum_{x \in \Omega} x \cdot p_X(x) = 1 \cdot \frac{1}{6} + 2 \cdot \frac{1}{6} + \dots + 5 \cdot \frac{1}{6} + 6 \cdot \frac{1}{6} = 3,5$$

# Expectation of a random variable

**Properties:** We encounter several important properties for the expectation, i.e.

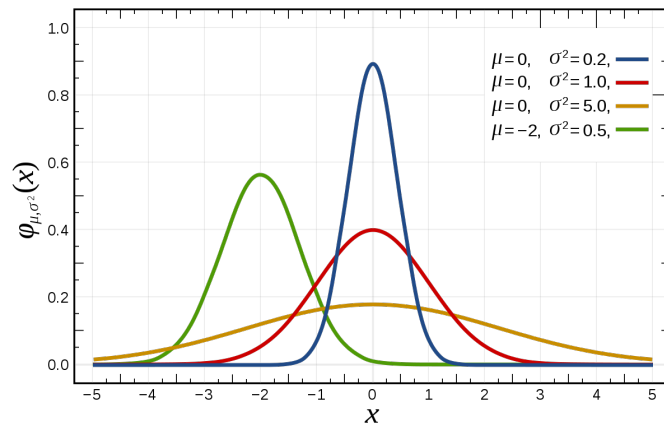
1.  $\mathbb{E}[a] = a$  for any constant  $a \in \mathbb{R}$
2. Linearity:  $\mathbb{E}[aX + bY] = a \cdot \mathbb{E}[X] + b \cdot \mathbb{E}[Y]$  for any constants  $a, b \in \mathbb{R}$

# Variance of a random variable

- **Idea:** The variance of a random variable is a measure how concentrated the distribution of a random variable  $X$  is around its mean.

- **Definition:** The variance is defined as

$$\begin{aligned}\text{Var}(X) &= \mathbb{E}[(X - \mathbb{E}[X])^2] \\ &= \mathbb{E}[X^2] - \mathbb{E}[X]^2\end{aligned}$$



# Variance of a random variable

**Definition:** The variance is defined as  $\text{Var}(X) = \mathbb{E}[(X - \mathbb{E}[X])^2] = \mathbb{E}[X^2] - \mathbb{E}[X]^2$

## Example: Tossing a fair six-sided die

$\Omega = \{1, 2, 3, 4, 5, 6\}$ ,  $X$ : represents the outcome of the toss

$$p_X(x) = \mathbb{P}(X = x) = \frac{1}{6} \forall x \in \Omega$$

$$\mathbb{E}[X] = 3,5, \mathbb{E}[X]^2 = 12\frac{1}{4}$$

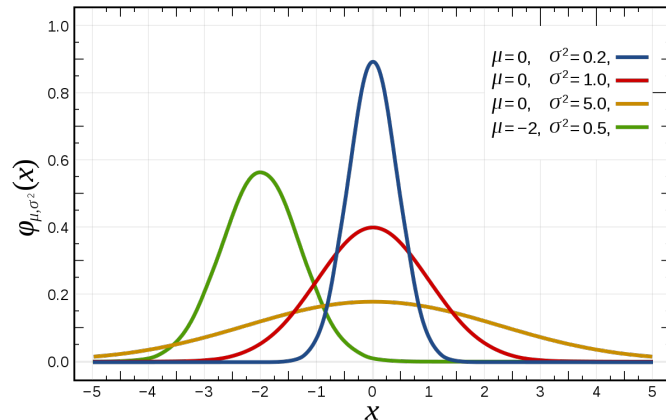
$$\mathbb{E}[X^2] = \sum_{x \in \Omega} x^2 \cdot p_X(x) = 1^2 \cdot \frac{1}{6} + 2^2 \cdot \frac{1}{6} + \dots + 5^2 \cdot \frac{1}{6} + 6^2 \cdot \frac{1}{6} = 15\frac{1}{6}$$

$$\text{Var}(X) = \mathbb{E}[X^2] - \mathbb{E}[X]^2 = 15\frac{1}{6} - 12\frac{1}{4} = \frac{35}{12} \approx 2,91$$

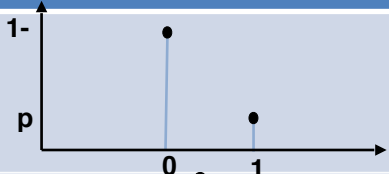
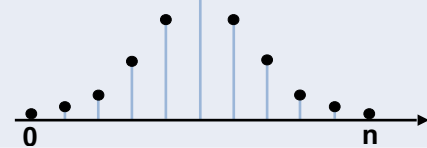

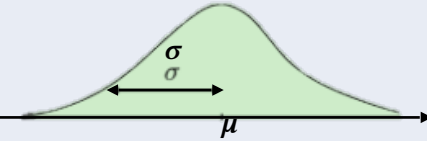


# Variance of a random variable

- **Properties:** The variance has the following properties, i.e.
  1.  $\text{Var}(a) = 0$  for any constant  $a \in \mathbb{R}$
  2.  $\text{Var}(a \cdot X + b) = a^2 \cdot \text{Var}(X)$



# Standard Probability Distributions

Distribution	Parameter & Notation	PDF or PMF	Mean	Variance	Illustration
Bernoulli distribution (Discrete)	$X \sim \text{Ber}(p)$ $0 \leq p \leq 1$	$p_X(k) = p^k(1-p)^{1-k}$	$\mathbb{E}[X] = p$	$\text{Var}(X) = p(1-p)$	
Binomial distribution (Discrete)	$X \sim \text{Bin}(n, p)$ $n \in \mathbb{N}, p \in [0, 1]$	$p_X(k) = \binom{n}{k} p^k (1-p)^{n-k}$	$\mathbb{E}[X] = n \cdot p$	$\text{Var}(X) = np(1-p)$	
Uniform distribution (Continuous)	$X \sim U(a, b)$ $-\infty < a < b < \infty$	$f_X(x) = \begin{cases} \frac{1}{(b-a)} & x \in [a, b] \\ 0 & \text{else} \end{cases}$	$\mathbb{E}[X] = \frac{1}{2}(a+b)$	$\text{Var}(X) = \frac{1}{12}(b-a)^2$	
Normal distribution (Continuous)	$X \sim \mathcal{N}(\mu, \sigma^2)$ $\mu \in \mathbb{R}, \sigma^2 \in \mathbb{R}_{\geq 0}$	$f_X(x) = \frac{1}{\sigma\sqrt{2\pi}} e^{-\frac{1}{2}\left(\frac{x-\mu}{\sigma}\right)^2}$	$\mathbb{E}[X] = \mu$	$\text{Var}(X) = \sigma^2$	

# References

- <http://cs229.stanford.edu/section/cs229-prob.pdf>
  - Comprehensive Probability Review – **recommended!**
- <https://stanford.edu/~shervine/teaching/cme-106/cheatsheet-probability>
  - Quick Overview
- <https://www.deeplearningbook.org/contents/prob.html>
  - Another great resource. Also covers information theory basics.