ECE499/ECE590
Machine Learning for Embedded Systems
(Fall 2021)

Lecture 1: Course Information and Introduction to Machine Learning

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Agenda

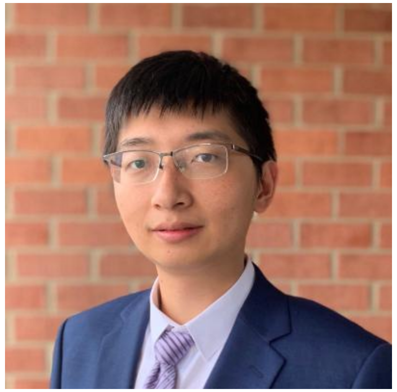
- Course Information
  - Logistics
  - Motivation
  - Overview
- Introduction to Artificial Neuron and MLP

Course Logistics

Course Resources

- **Course Website:**
  - https://jqub.github.io/2021/09/01/ML4Emb/
  - Slides, readings, and documents will be posted here!
  - Assignments will be posted here! (Until Blackboard can be used)
- **Blackboard:**
  - Assignments will be posted and submitted here!
- **Piazza:**
  - Online discussion, shared documents, announcements.
  - Do NOT upload codes.

About Me.



Dr. Weiwen Jiang

- **Background**
  - Researcher at University of Pittsburgh (2017-2019)
  - Postdoc at University of Notre Dame (2019-2021)
  - George Mason University (2021 - present)
- **Research Interests**
  - HW/SW Co-Design
  - Quantum Machine Learning
- **Contacts:**
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  - (412)427-0695
  - https://jqub.github.io/

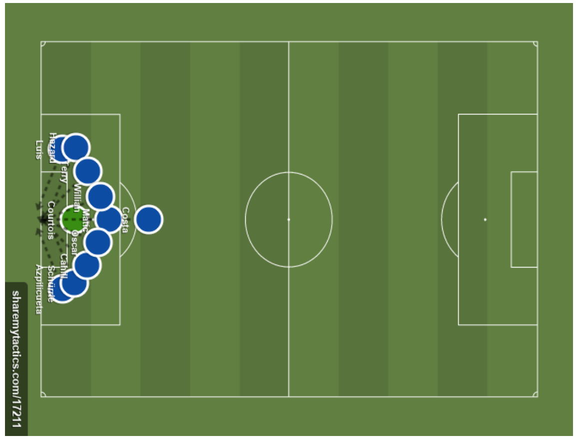
Teaching Assistant

XXX

XXX@gmu.edu

Office Hours: TBD

Lecture-Presentation-Lab Hours



10-0-0
(No!)

4-3-3
(Yes!)

Good Stuff

- No quizzes
- No mid-terms
- No finals
- Contents driven by demand and interest

"Bad" Stuff

- You'll have to make presentation or critiques
- You'll have to hand-on labs
- You'll have to work on a final project

- Eventually, they will do you good!

Grading Policy

Undergraduate (ECE 499)

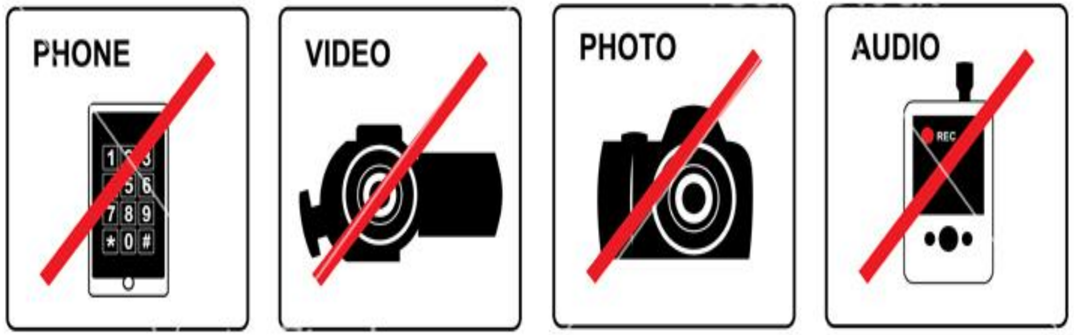
• Homework & Labs	50%
• Paper Critiques	10%
• Project progress review	10%
• Project final review	30%

Graduate (ECE 590)

• Homework & Labs	50%
• Research paper presentation	20%
• Project progress review	10%
• Project final review/report	20%

You have been warned.
Zero tolerance!

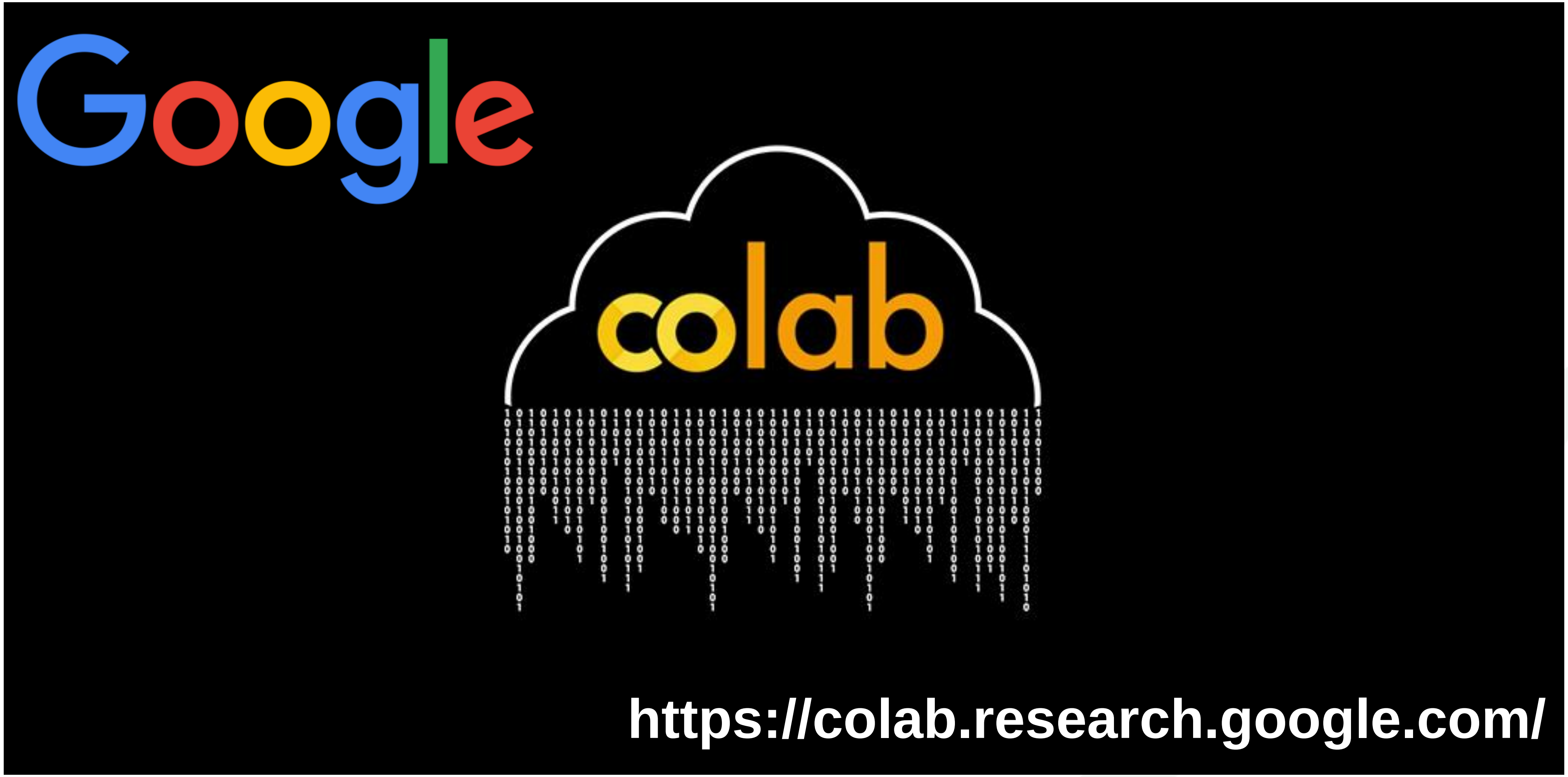
- **Lecture content and materials should NOT go online without explicit permission**



- **No plagiarism!**

The most common sense of way interpreting no plagiarism:
You need to DO your work.

ML Programming Platform



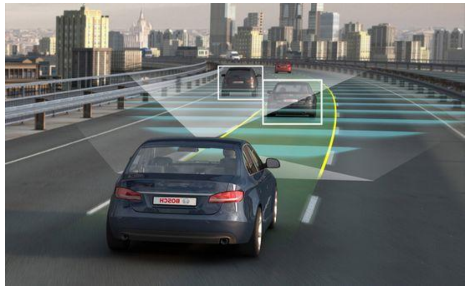
Course Motivation


"MACHINE LEARNING WILL
AUTOMATE JOBS THAT
MOST PEOPLE THOUGHT COULD ONLY BE
DONE BY PEOPLE." ~DAVE WATERS.

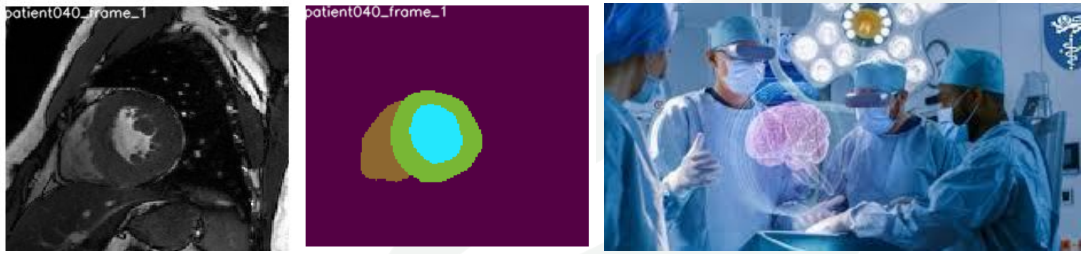
ML Applications

Game Play

Autonomous Driving

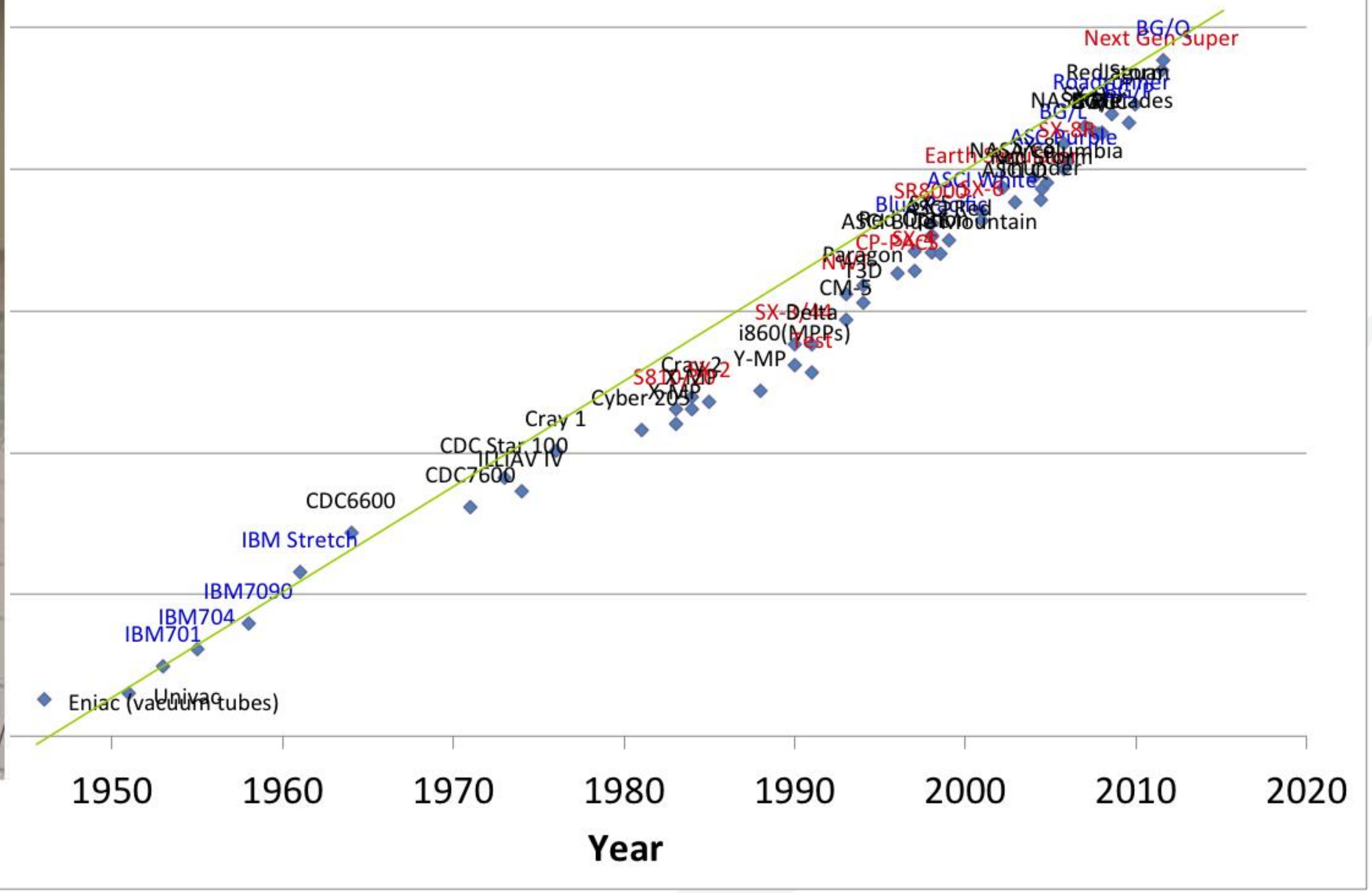


Medical AI

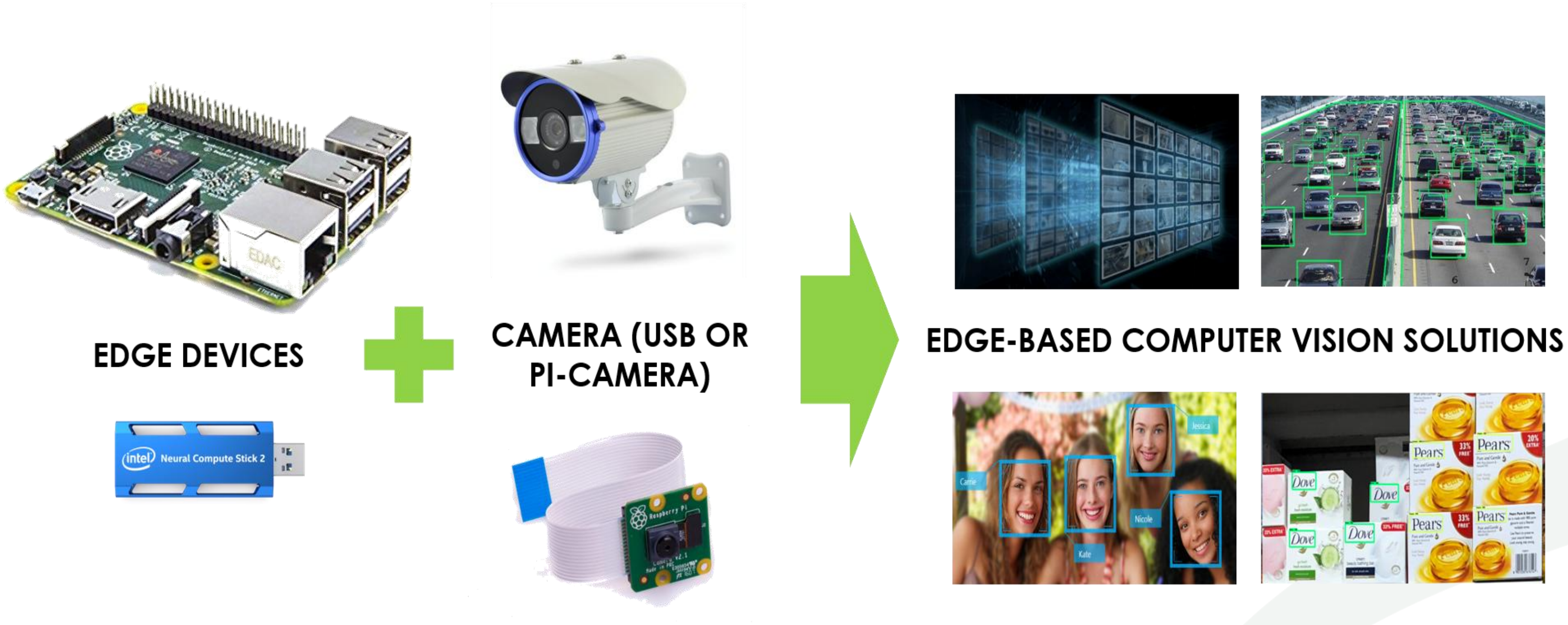


Race of Computer Powers Enables ML

Credit: IBM Blue Gene/Q Supercomputer



Machine Learning on the Edge



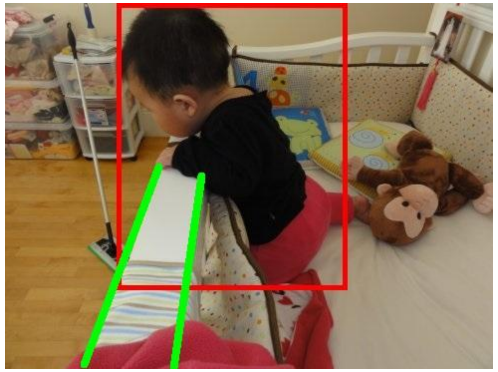
StrataHive
Enhancing the Digital Experience

Why on the Edge?

- Latency Problem

- Delay & Latency
- Speed
- WiFi Access

- Privacy Leakage



- Data uploaded to the server
- Privacy concerns

- Cost/energy efficiency considerations

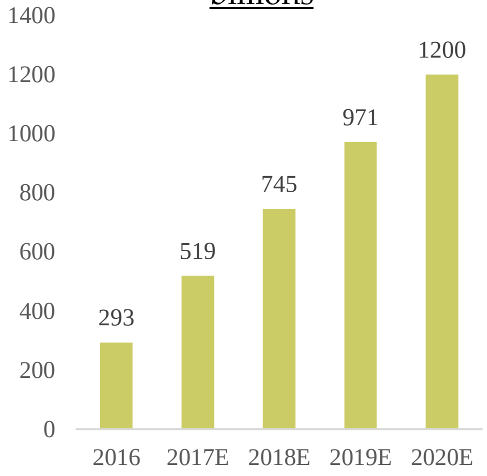
Why on the Edge?

AI chip bearing artificial intelligence algorithm, billion dollar market opportunity

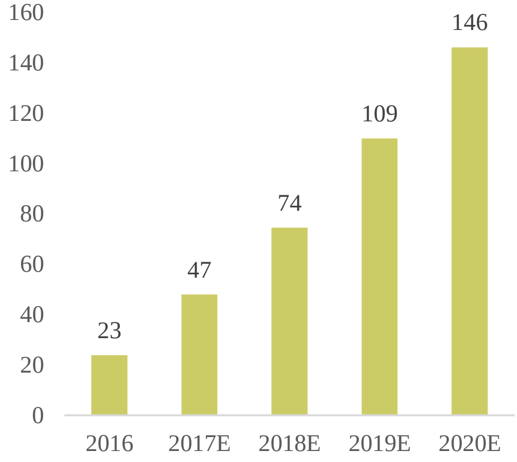
Big data, Maturing algorithm,
Core processor for AI Chip is the key

- **Data**
  - Massie data and frequent human computer interaction
- **Calculation**
  - Engineering methods and simulation methods require the use of convolutions.
- **Hardware**
  - Insufficient calculation, AI chips provide computing power: GPU, FPGA, ASIC, TPU

Global AI market exceeds US$100 billions



AI chip market will exceed US$10 billions



14.6 billions

Smart end devices

Apple, Qualcomm, Spreadtrum, HiSilicon, Mediatek, annual volume

9 billions

Home appliance

Smart appliance, digital TV, set top box, game console, VR/AR annual volume

200+ billions

Autopilot

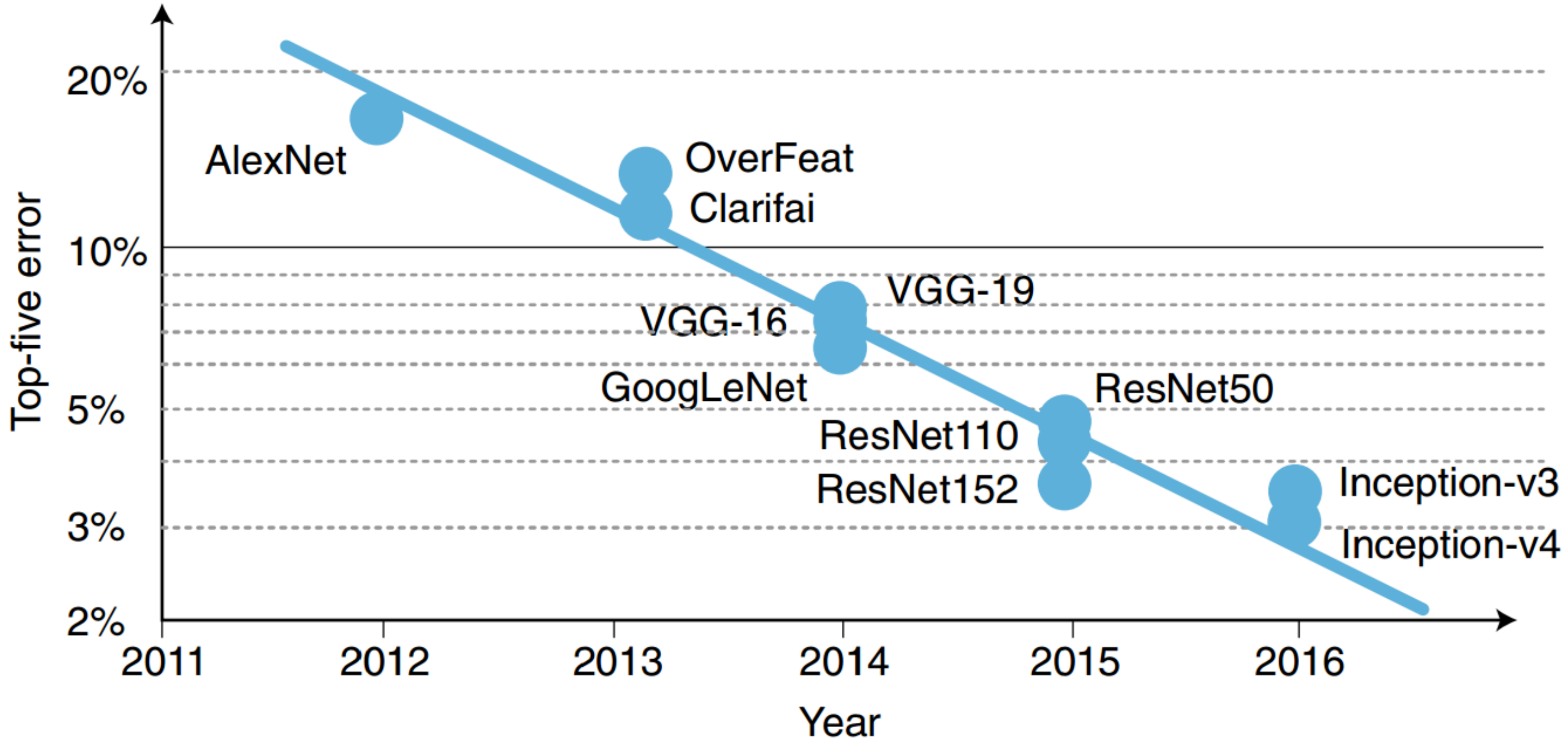
ADAS chip market potential

Global AI Chip Market is Expanding!

Source: CCID, NVIDIA, Intel, gartner, CITIC Securities

Challenges of ML on Edge

Error rate improved exponentially

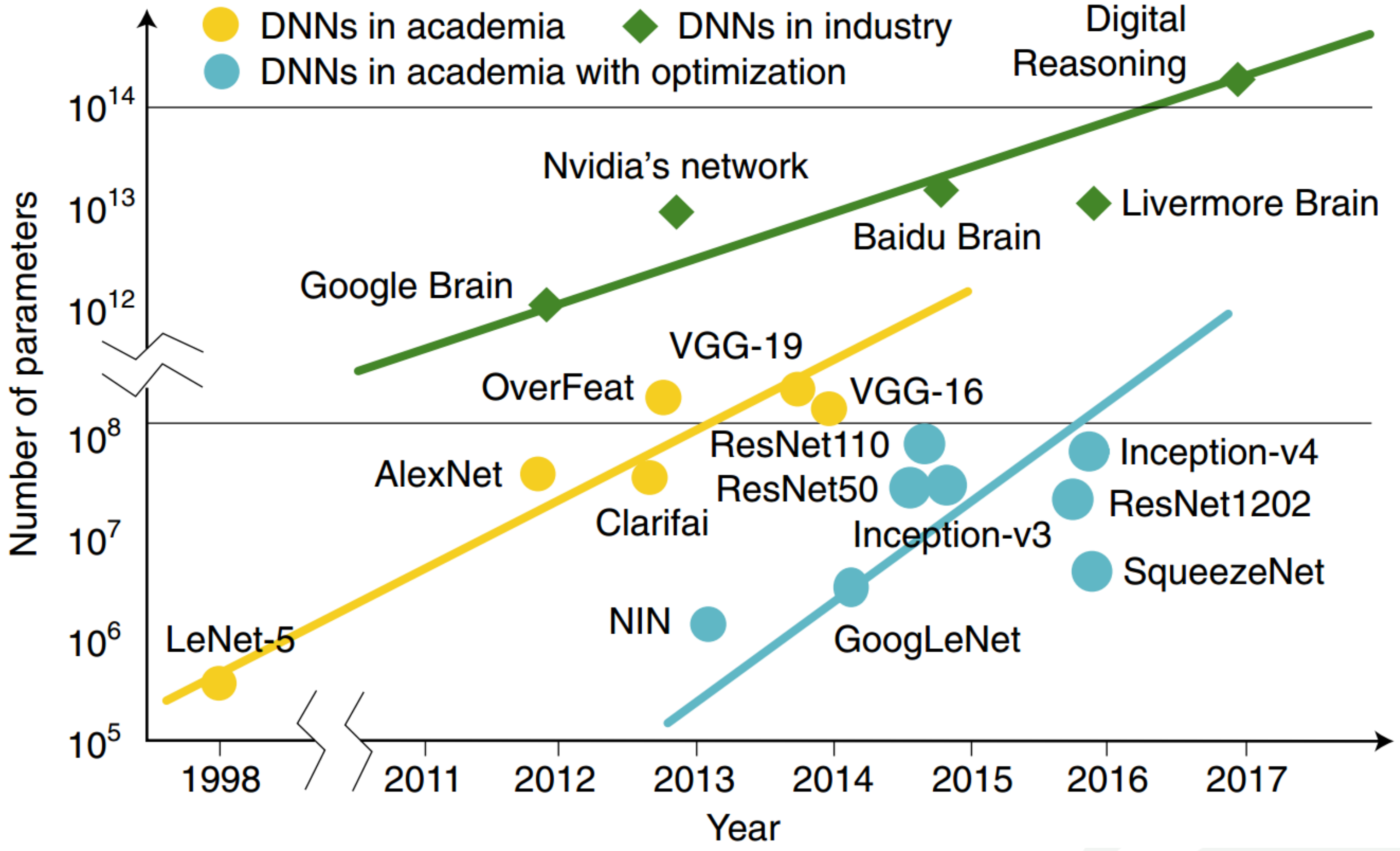


Error rate decreases by approximately 30% each year

Xu, Xiaowei, et al. "Scaling for edge inference of deep neural networks." Nature Electronics 1.4 (2018): 216.

Challenges of ML on Edge

Size of machine learning model also increases exponentially

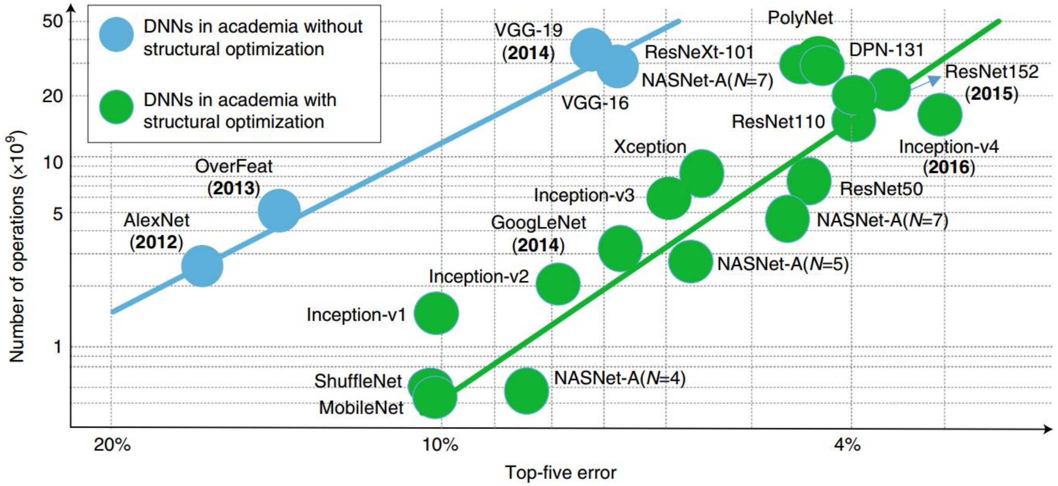


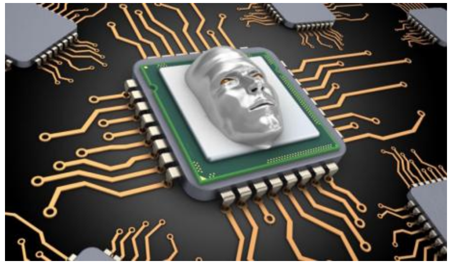
Xu, Xiaowei, et al. "Scaling for edge inference of deep neural networks." Nature Electronics 1.4 (2018): 216.

Challenges of ML on Edge

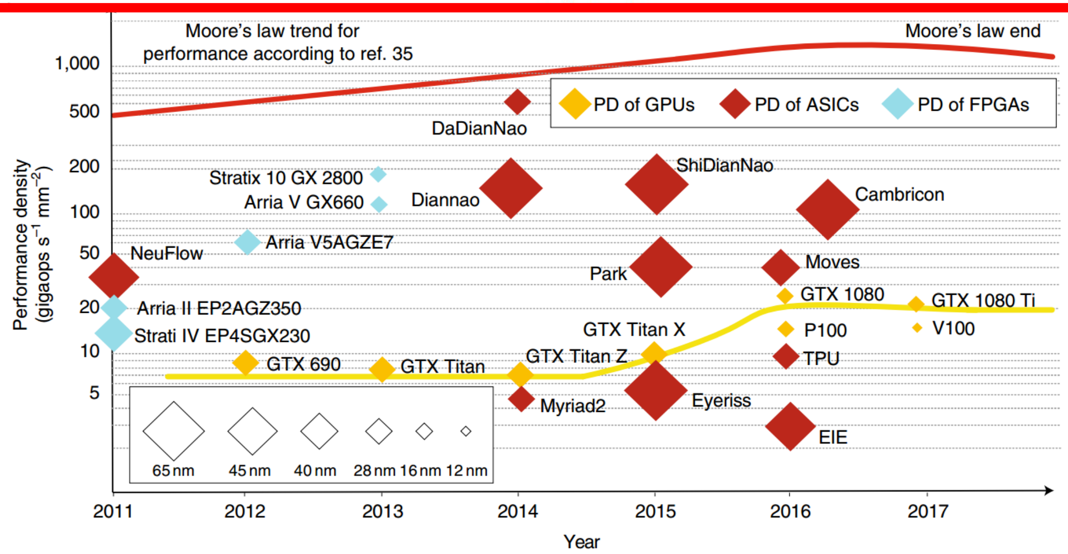
Computing performance gap

Number of DNN **operations** increases exponentially





Performance density almost stops increasing



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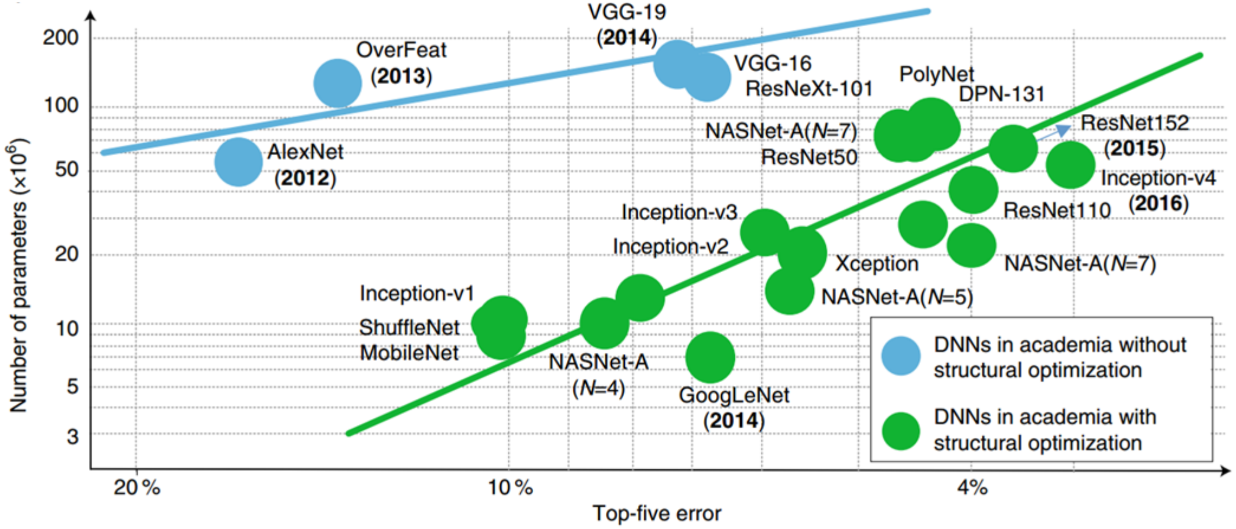
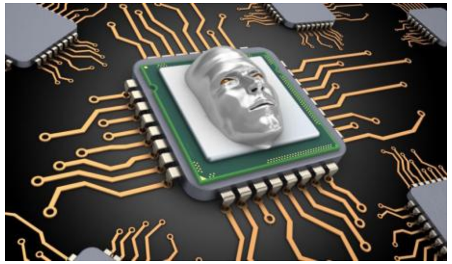
Challenges of ML on Edge

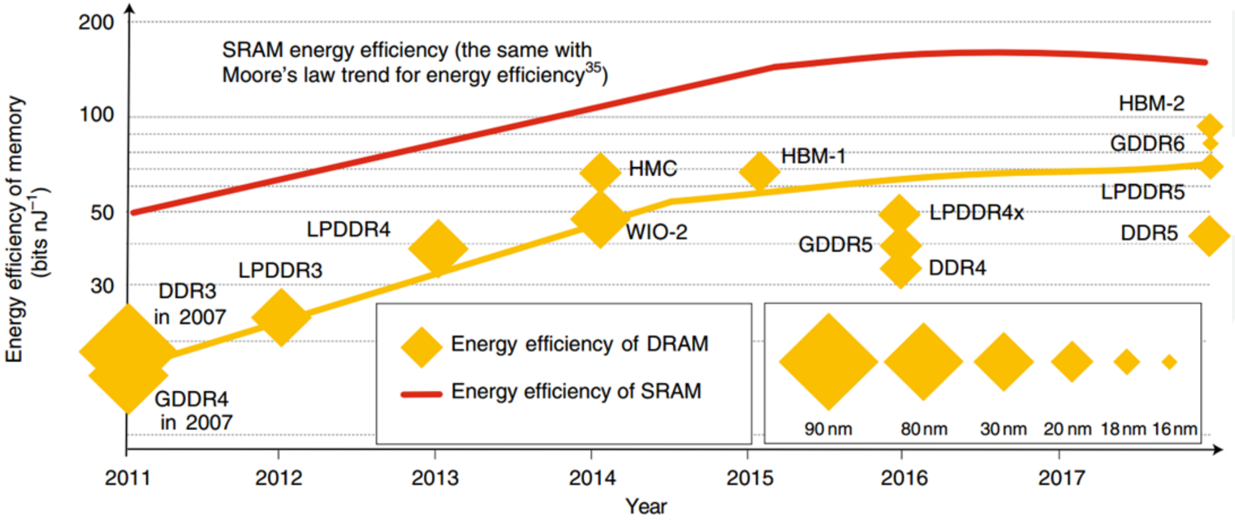
Storage energy efficiency gap

Number of DNN **parameters** increases exponentially





Energy efficiency of memory almost stops increasing

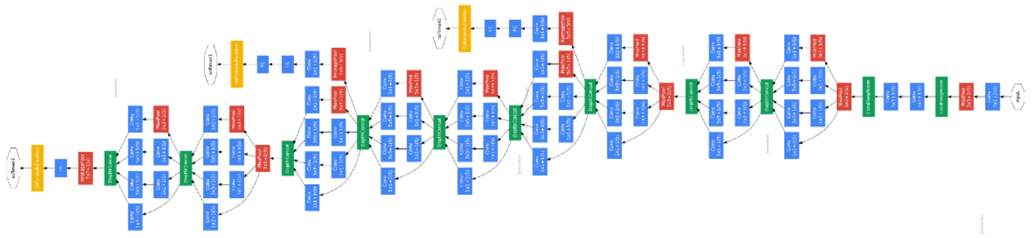


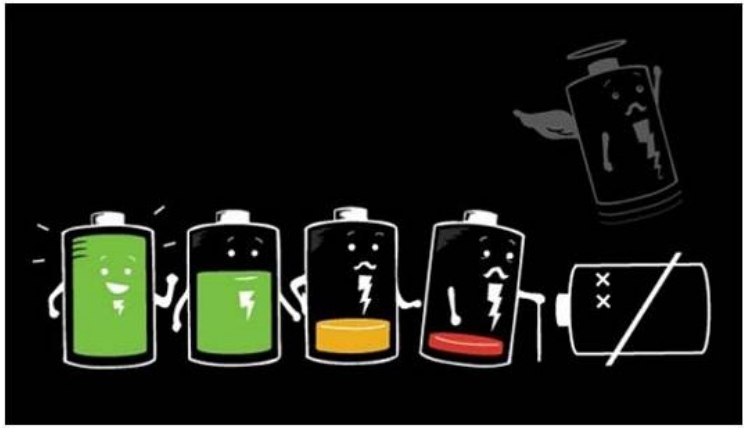
Xu, Xiaowei, et al. "Scaling for edge inference of deep neural networks." Nature Electronics 1.4 (2018): 216.

Course Overview

What is This Course About?

Open question on Machine Learning for Embedded Systems!





Machine Learning

- High computation complexity
- High storage complexity

V.S.

Embedded Systems

- Low power
- Small on-chip memory
- Low bandwidth
- Real-time requirements

How to overcome the limitations of embedded systems?

What is This Course About?

Software side: AI/ML/DL?

Artificial Intelligence (AI)

[Definition] AI is intelligence demonstrated by machines, unlike the natural intelligence displayed by humans and animals, which involves consciousness and emotionality.

What is This Course About?

Software side: AI/ML/DL?

Artificial Intelligence (AI)

Machine Learning (ML)

[Definition] ML is the study of computer algorithms that improve automatically through experience and by the use of data. It is seen as a part of AI.

ECE 527: Learning From Data

What is This Course About?

Software side: AI/ML/DL?

Artificial Intelligence (AI)

Machine Learning (ML)

Deep Learning (DL)

[Definition] DL is a class of ML Algorithms that uses multiple layers to progressively extract higher-level features from the raw input.

- Computer Vision
- Natural Language
- Games
- …

What is This Course About?

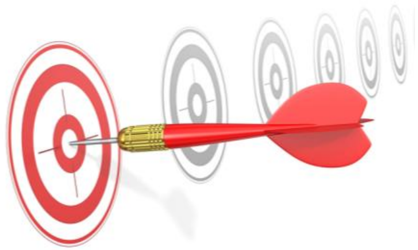
Overview: software side

Software

Application
- Computer Vision
- Natural Language
- Games
- …

ML/DL Algorithms
- AN
- MLP
- CNN
- RNN
- LSTM
- RL
- Transformer
- MLP-Mixer
- …

Optimization
- Network Inference
- Network Training



High Accuracy

What is This Course About?

Hardware side: from cloud to edge

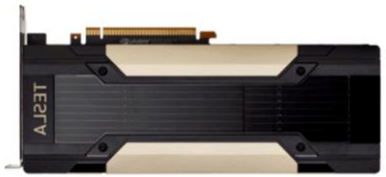
ECE 350: Embedded Systems and Hardware Interfaces

Mobile Device

Microcontroller

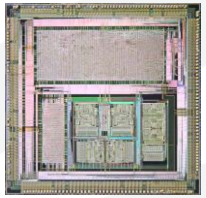
General Purpose Computing

Cloud GPU/CPU



Customized Computing

FPGA
Field-Programmable Gate Array



ASIC
Application Specifical Integrate Circuit

ECE 231: Digital System Design

What is This Course About?

Overview

Software

Application

- Computer Vision
- Natural Language
- Games
- …

ML/DL Algorithms

AN | MLP | CNN
RNN | LSTM | RL
Transformer | MLP-Mixer
…

Optimization

- Network Inference
- Network Training
- Model Compression
- Network Design

Hardware

Embedded Systems

ECE 699: Hardware Accelerators for Machine Learning

Low-Power 

 **Low-Latency**

What is This Course About?

Overview

Software

Hardware

Application

- Computer Vision
- Natural Language
- Games
- …

ML/DL Algorithms

- AN
- MLP
- CNN
- RNN
- LSTM
- RL
- Transformer
- MLP-Mixer
- …

Optimization

- Network Inference
- Network Training
- Model Compression
- Network Design

Embedded Systems

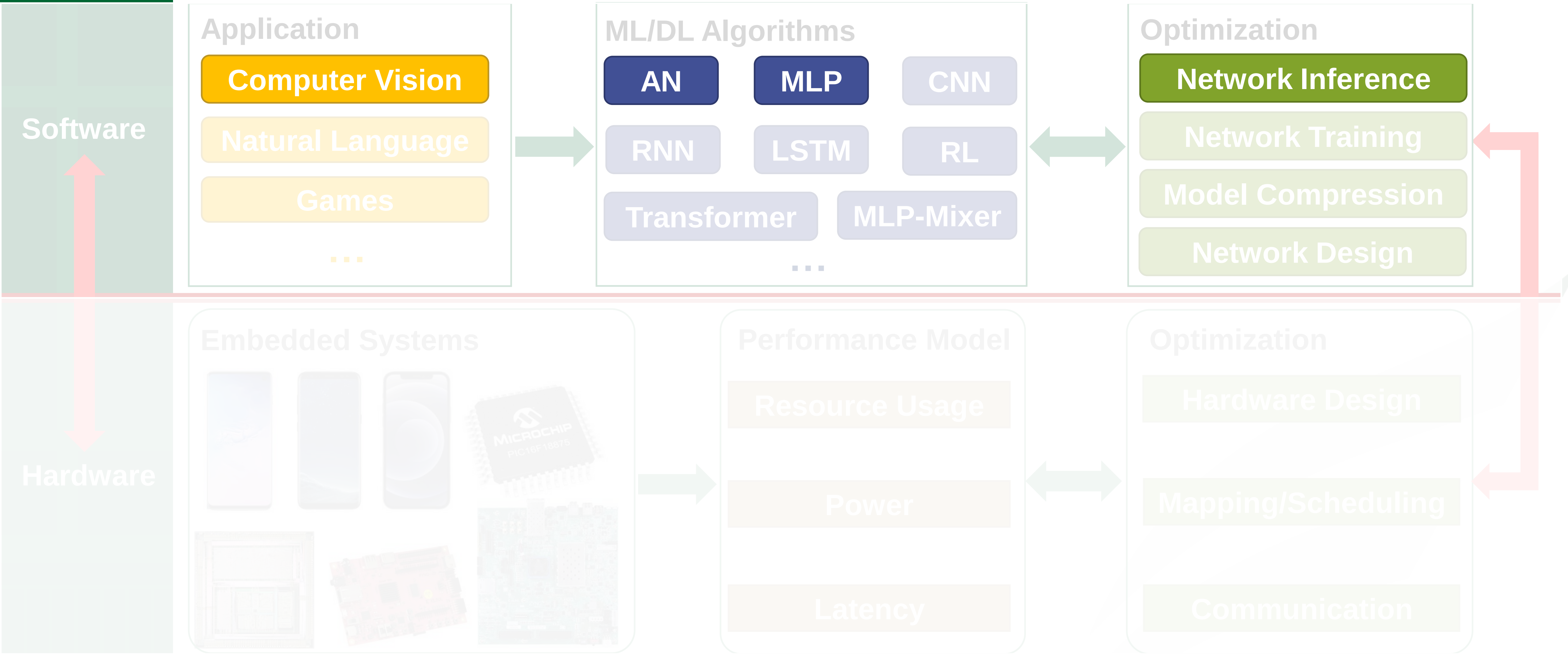
Performance Model

- Resource Usage
- Power
- Latency

Optimization

- Hardware Design
- Mapping/Scheduling
- Communication

Week 1: Introduction to Artificial Neuron and MLP



Week 2: From Inference to Training, From MLP to CNN

Software

Hardware

Application
- Computer Vision
- Natural Language
- Games
- ...

ML/DL Algorithms
- AN
- MLP
- CNN
- RNN
- LSTM
- RL
- Transformer
- MLP-Mixer
- ...

Optimization
- Network Inference
- Network Training
- Model Compression
- Network Design

Embedded Systems

Performance Model
- Resource Usage
- Power
- Latency

Optimization
- Hardware Design
- Mapping/Scheduling
- Communication

Week 3-4: From CV to NLP

Software

Application
- Computer Vision
- **Natural Language**
- Games
- ...

ML/DL Algorithms
- AN
- MLP
- CNN
- **RNN**
- **LSTM**
- RL
- **Transformer**
- MLP-Mixer
- ...

Optimization
- **Network Inference**
- **Network Training**
- Model Compression
- Network Design

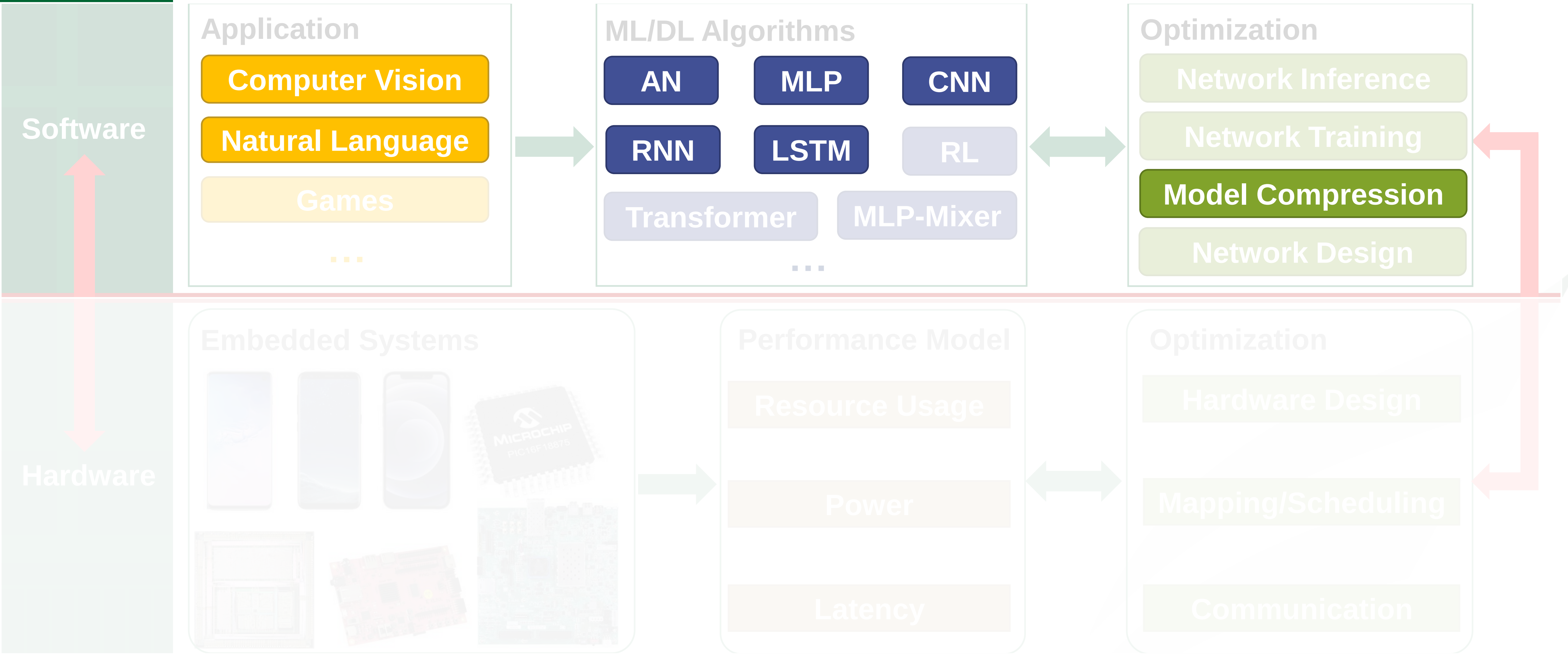
Hardware

Embedded Systems

Performance Model
- Resource Usage
- Power
- Latency

Optimization
- Hardware Design
- Mapping/Scheduling
- Communication

Week 5-6: Model Compression



Week 7: From Deep Learning to Deep Reinforcement Learning

Software

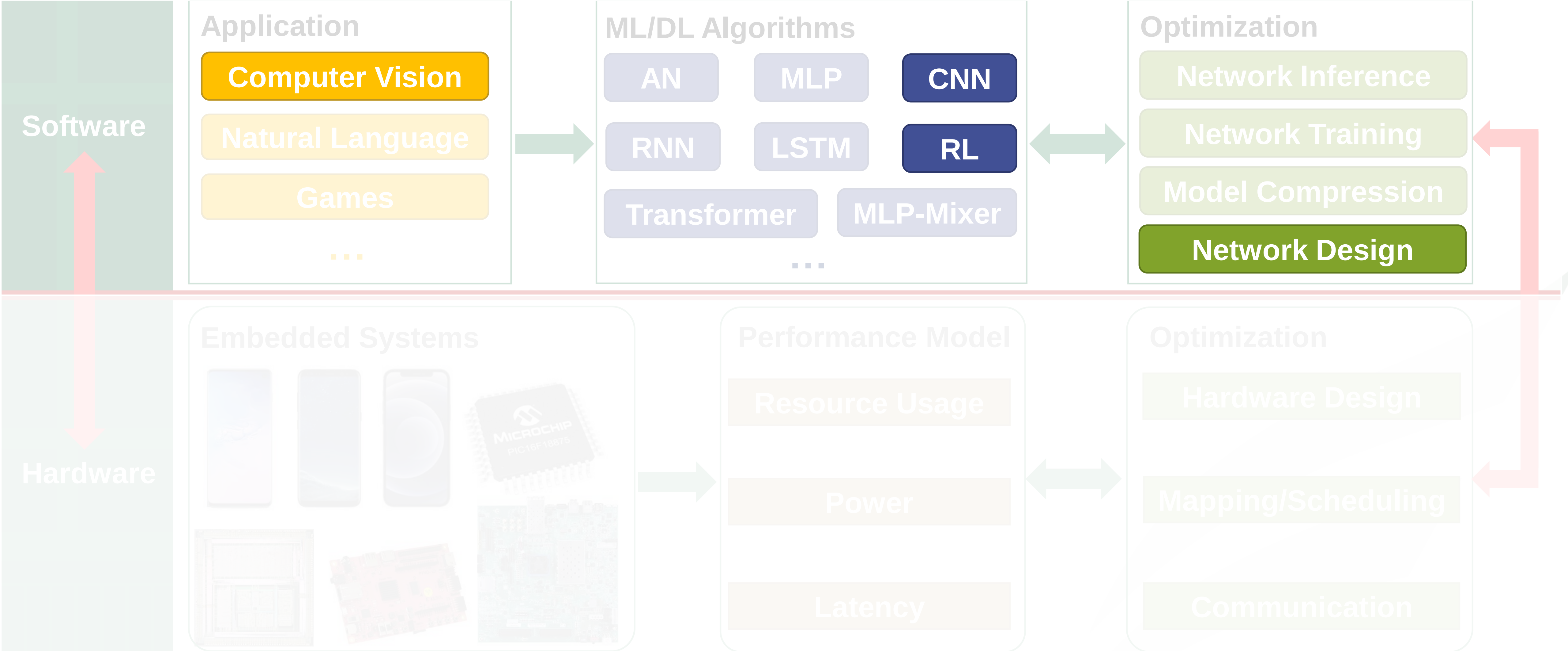
- Application
  - Computer Vision
  - Natural Language
  - **Games**
  - ...
- ML/DL Algorithms
  - AN
  - MLP
  - CNN
  - RNN
  - LSTM
  - **RL**
  - Transformer
  - MLP-Mixer
  - ...
- Optimization
  - **Network Inference**
  - **Network Training**
  - Model Compression
  - Network Design

Hardware

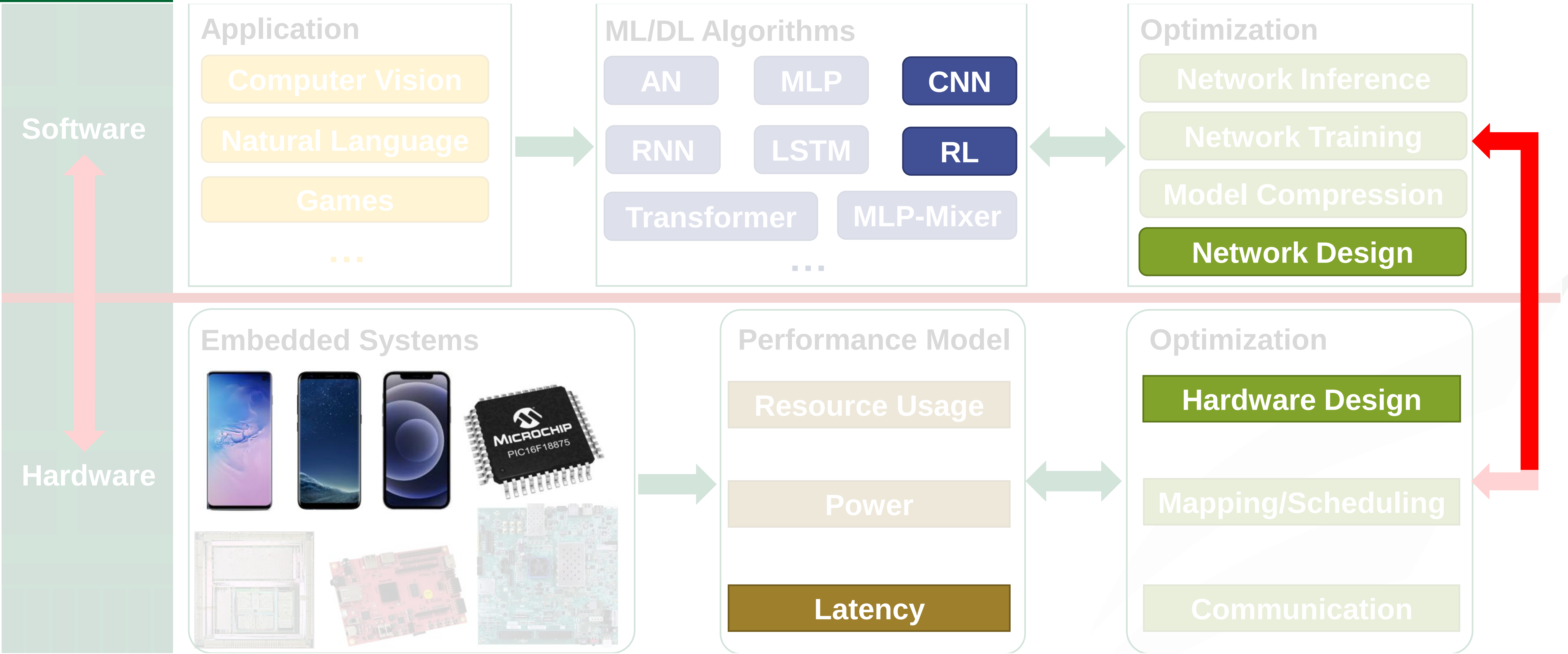
- Embedded Systems

- Performance Model
  - Resource Usage
  - Power
  - Latency
- Optimization
  - Hardware Design
  - Mapping/Scheduling
  - Communication

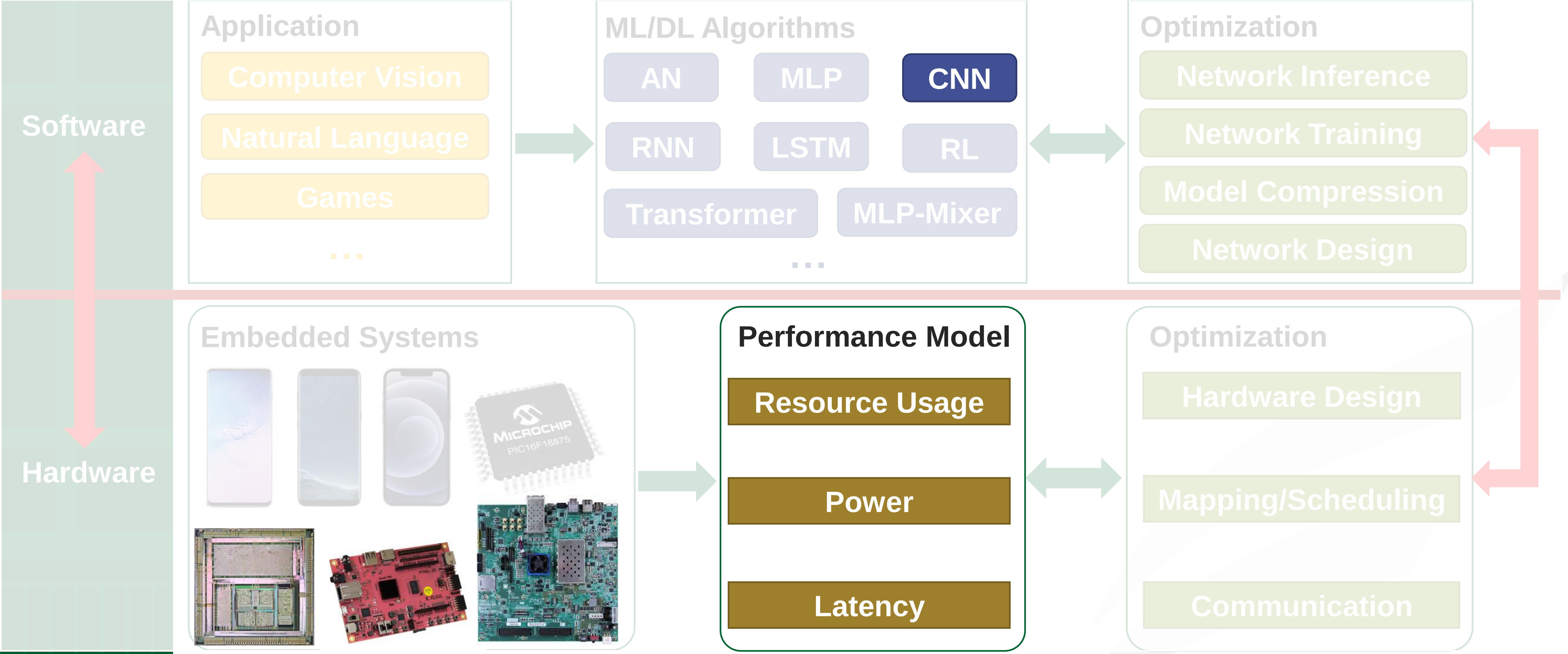
Week 8: RL-based Network Design (Neural Architecture Search)



Week 9: Hardware-Aware Neural Architecture Search



Week 10-11: ML Accelerator Design



Week 12-14: HW/SW Co-Design with Neural Architecture Search

Software

Hardware

Application

Computer Vision

Natural Language

Games

...

ML/DL Algorithms

AN | MLP | CNN

RNN | LSTM | RL

Transformer | MLP-Mixer

...

Optimization

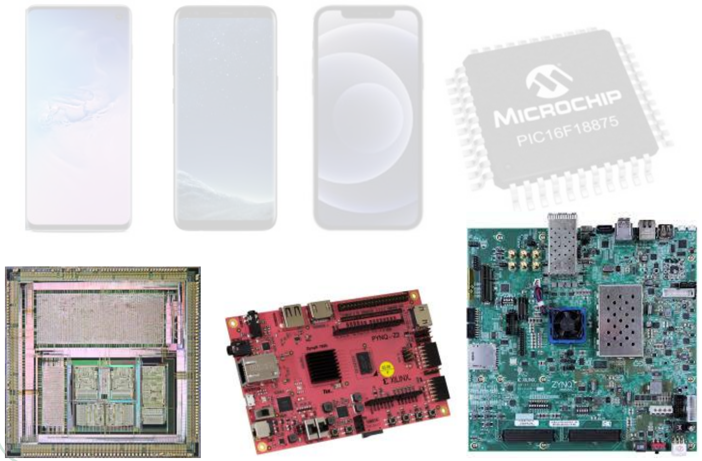
Network Inference

Network Training

Model Compression

Network Design

Embedded Systems



Performance Model

Resource Usage

Power

Latency

Optimization

Hardware Design

Mapping/Scheduling

Communication

Introduction to Artificial Neuron and MLP

Week 1: Introduction to Neural Network

Software

Application
- Computer Vision
- Natural Language
- Games
- ...

ML/DL Algorithms
- AN
- MLP
- CNN
- RNN
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- ...

Optimization
- Network Inference
- Network Training
- Model Compression
- Network Design

Hardware

Embedded Systems

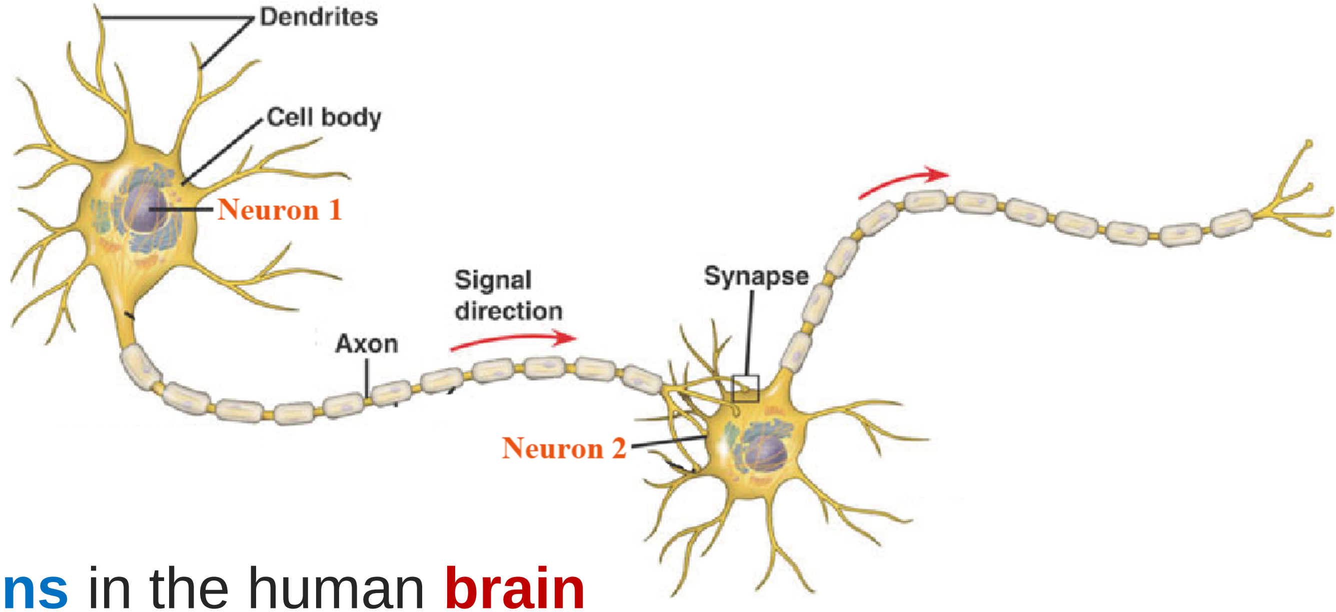
Performance Model
- Resource Usage
- Power
- Latency

Optimization
- Hardware Design
- Mapping/Scheduling
- Communication

Why Neural Networks

- **An emulation of the biological neural systems**
  - Parallel computation
  - Adaptive connections
- **Very different style from sequential computation**
  - Should be good for things that brains are good at (e.g., vision)
  - Should be bad for things that brains are bad at (e.g., 23 x 71)
- **To solve practical problems by using novel learning algorithms inspired by the brain**
  - Learning algorithms can be very useful even if they are not how the brain actually works.

Biological Neuron



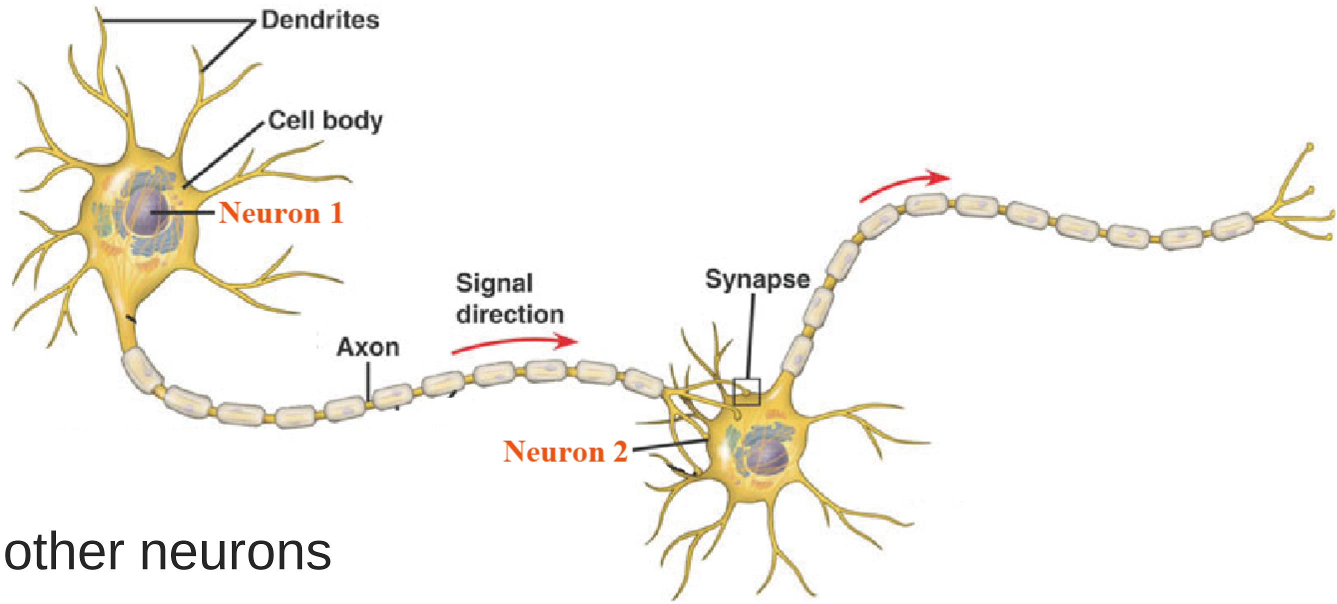
Human intelligence reside in the brain:

- Approximately **86 billion neurons** in the human **brain**
- The brain is a **network** of **neurons**, connected with nearly $10^{14} - 10^{15}$ **synapses**

How to equip intelligence in the machine?

- **To understand how the brain network is constructed**
- **To mimic the brain**

Biological Neuron



Neurons work together:

- **Cell body** process the information
- **Dendrites** receive messages from other neurons
- **Axon** transmit the output to many smaller branches
- **Synapses** are the contact points between axon (Neuron 1) and dendrites (Neuron 2) for message passing

Cell body receives input signal from **dendrites** and produce output signal along **axon**, which interact with the next neurons via **synaptic weights**

Synaptic weights are **learnable** to perform useful computations

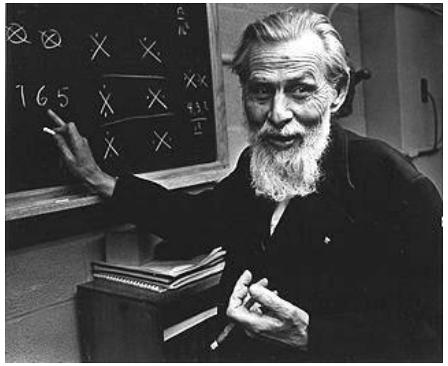
(e.g., Recognizing objects, understanding language, making plans, controlling the body.)

Artificial Neuron Design

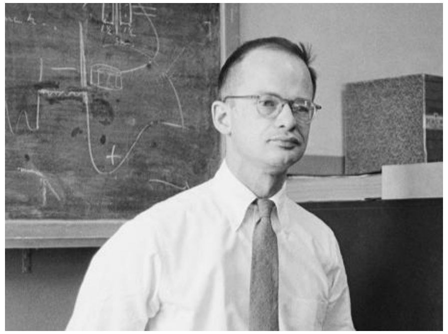
- **Idealized neuron models**
  - Idealization removes complicated details that are not essential for understanding the main principles.
  - It allows us to apply mathematics and to make analogies.

McCulloch-Pitts Neuron

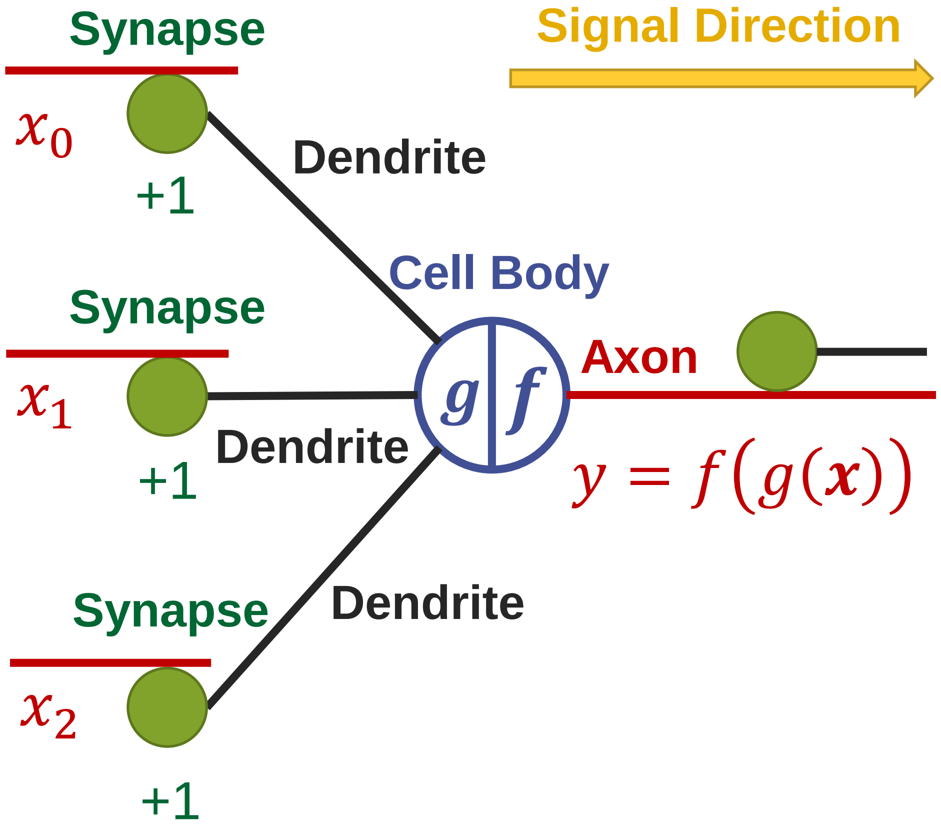
The first computational model of a biological neuron @ 1943



Warren McCulloch

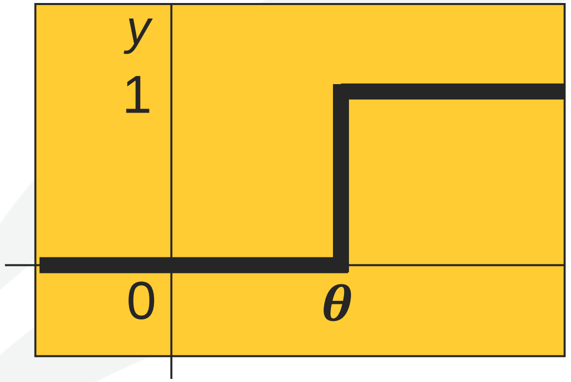


Walter Pitts



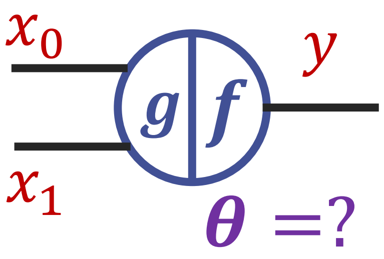
Assumptions:

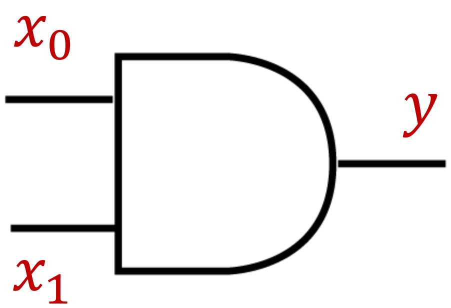
- Binary devices (i.e., $x_i \in \{0,1\}$ and $y \in \{0,1\}$)
- Identical synaptic weights (i.e., +1)
- Activation function f has a fixed threshold $\boldsymbol{\theta}$



McCulloch-Pitts Neuron

Boolean function 'AND' can be implemented by using MP Neuron



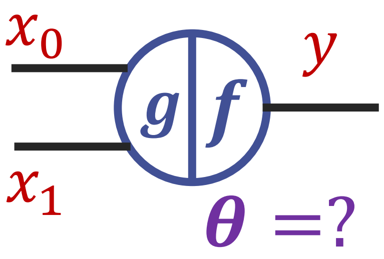


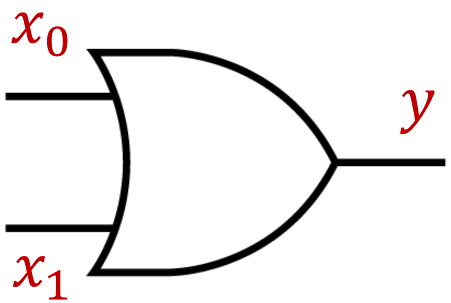
AND Gate

x_0	x_1	y
0	0	0
0	1	0
1	0	0
1	1	1

McCulloch-Pitts Neuron

Boolean function ‘OR’ can be implemented by using MP Neuron



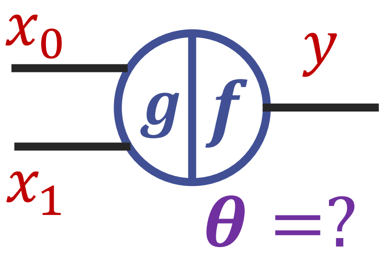


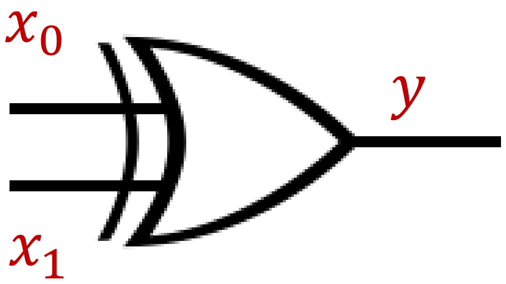
OR Gate

x_0	x_1	y
0	0	0
0	1	1
1	0	1
1	1	1

McCulloch-Pitts Neuron

Boolean function XOR cannot be implemented by using MP Neuron





XOR Gate

x_0	x_1	y
0	0	0
0	1	1
1	0	1
1	1	0

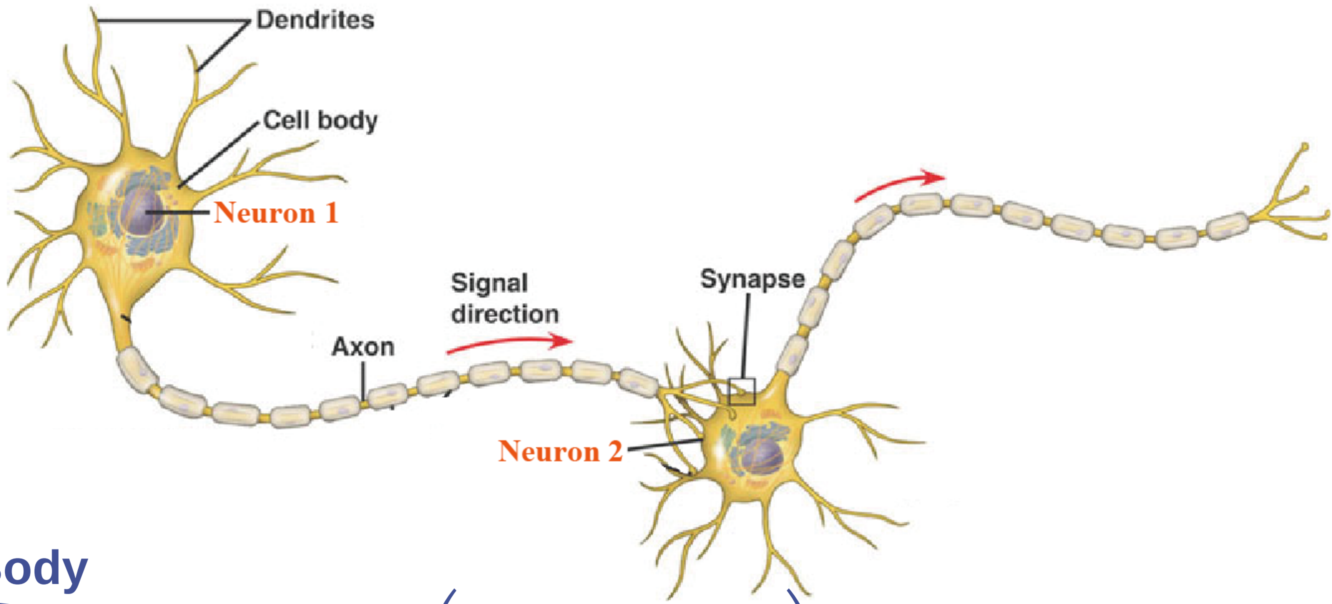
MP Neuron is limited to only solve linearly separable functions!

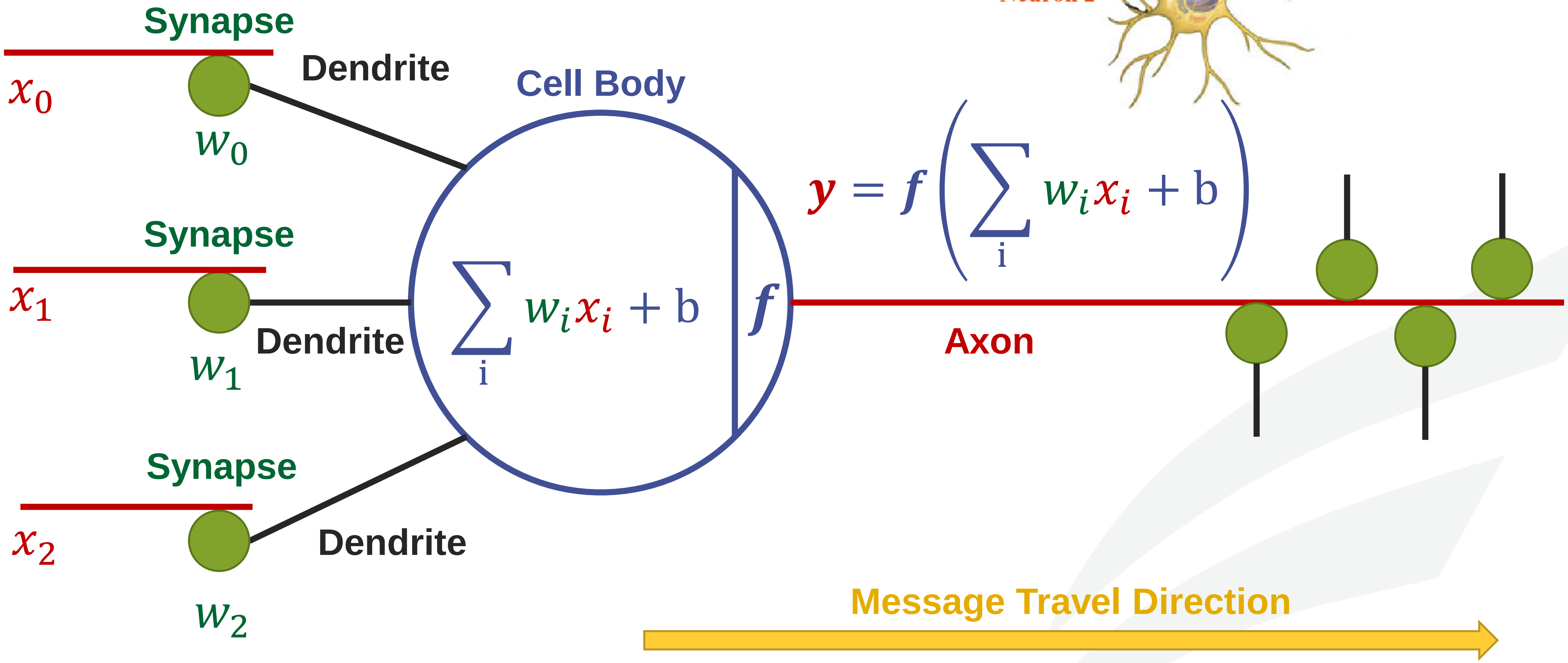
Artificial Neuron Design

- **Idealized neuron models**
  - Idealization removes complicated details that are not essential for understanding the main principles.
  - It allows us to apply mathematics and to make analogies.
- **Break the limitations on MP Neuron**
  - What about non-boolean inputs (say, real number)?
  - What if we want to assign more weight (importance) to some inputs?
  - Do we always need to hand code the threshold?
  - What about activation functions other than threshold step function?
  - What about functions which are not linearly separable ?

Perceptron

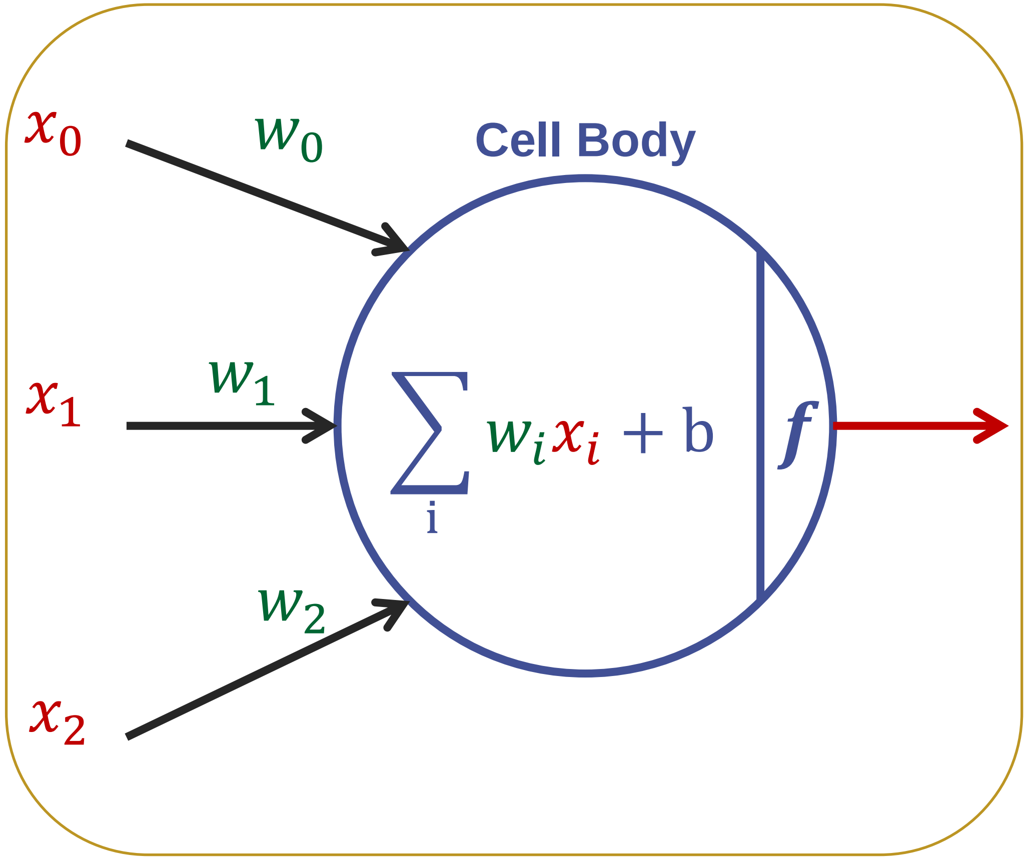
Frank Rosenblatt @ 1958

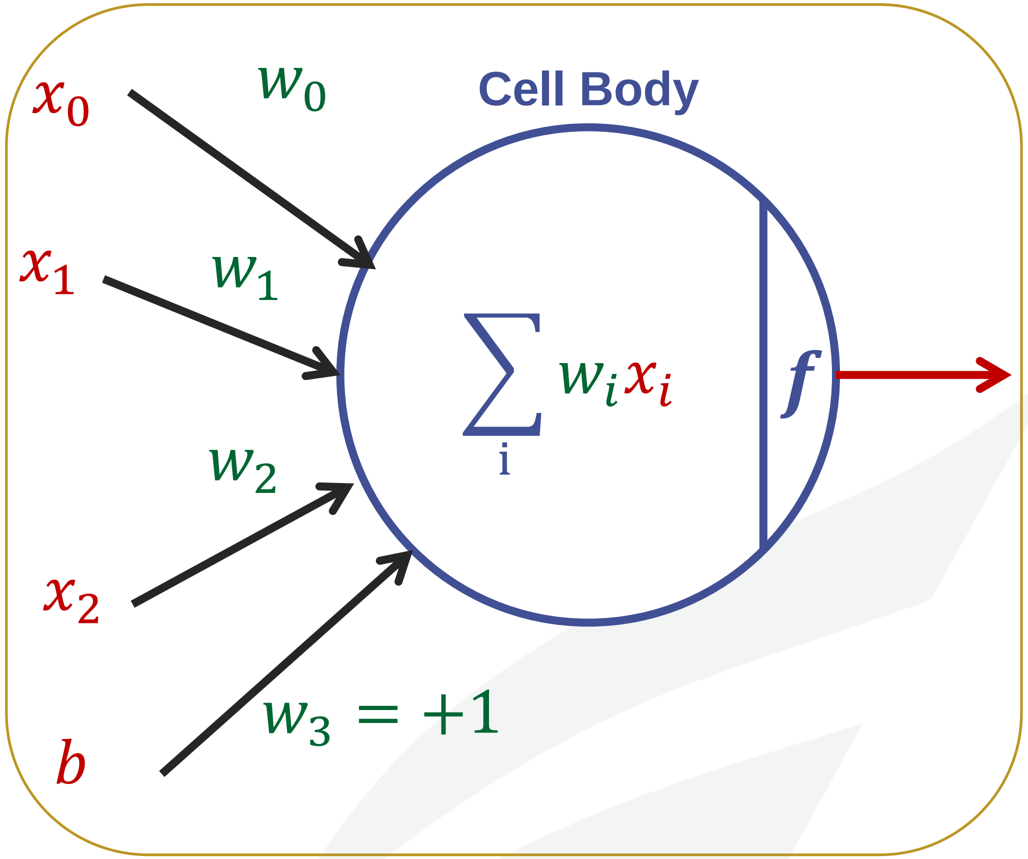




Perceptron

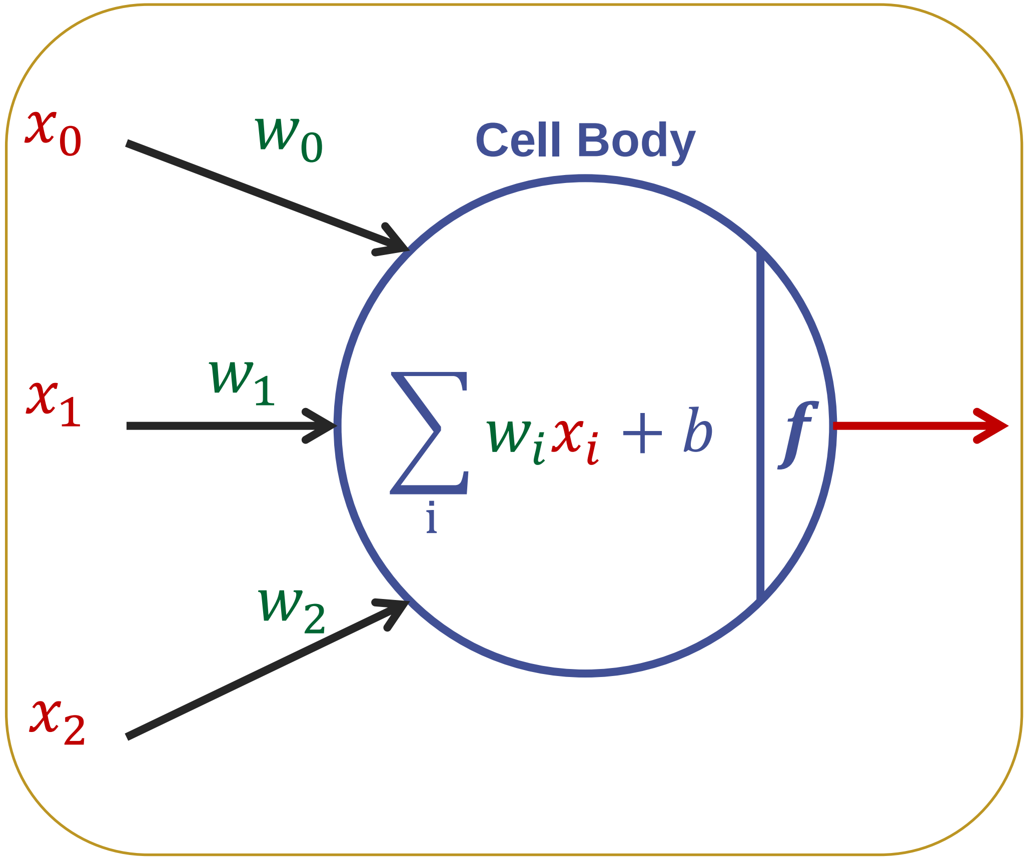
What is Bias b?

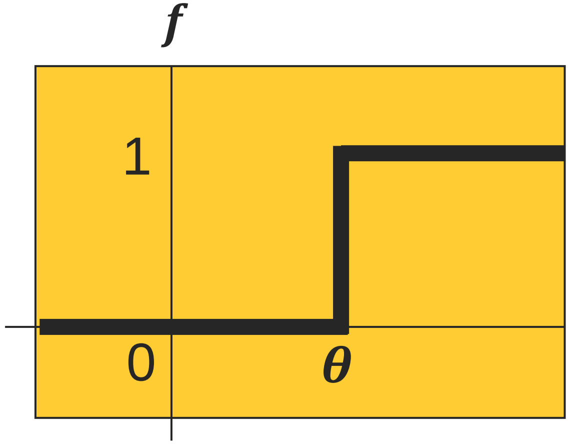




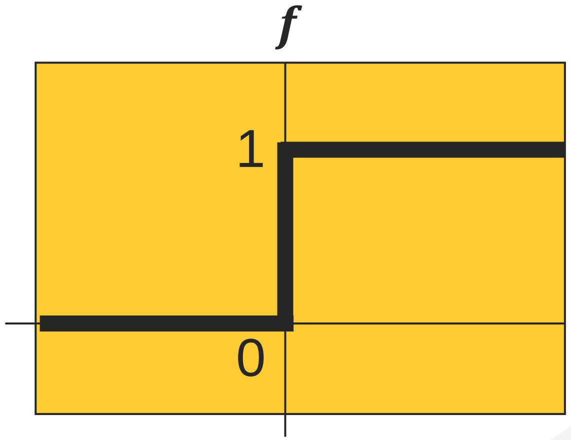
Perceptron

Effect of bias b on Threshold Step activation function.





$$b = 0$$



$$b = -\theta$$

$$z = \sum_i x_i w_i$$

$$z = \sum_i x_i w_i - \theta$$

$$y = \begin{cases} 1 & if\ z > \theta \\ 0 & otherwise \end{cases}$$

$$y = \begin{cases} 1 & if\ z > \mathbf{0} \\ 0 & otherwise \end{cases}$$

Perceptron v.s. MP Neuron

Perceptron

$$y = \begin{cases} 1 & if \sum_{i} x_i w_i + b > \mathbf{0} \\ 0 & otherwise \end{cases}$$

MP Neuron

$$y = \begin{cases} 1 & if \sum_{i} x_i > \theta \\ 0 & otherwise \end{cases}$$

In Perceptron: the inputs can be **real numbers;** the weights (including threshold) can be **learned/trained.**

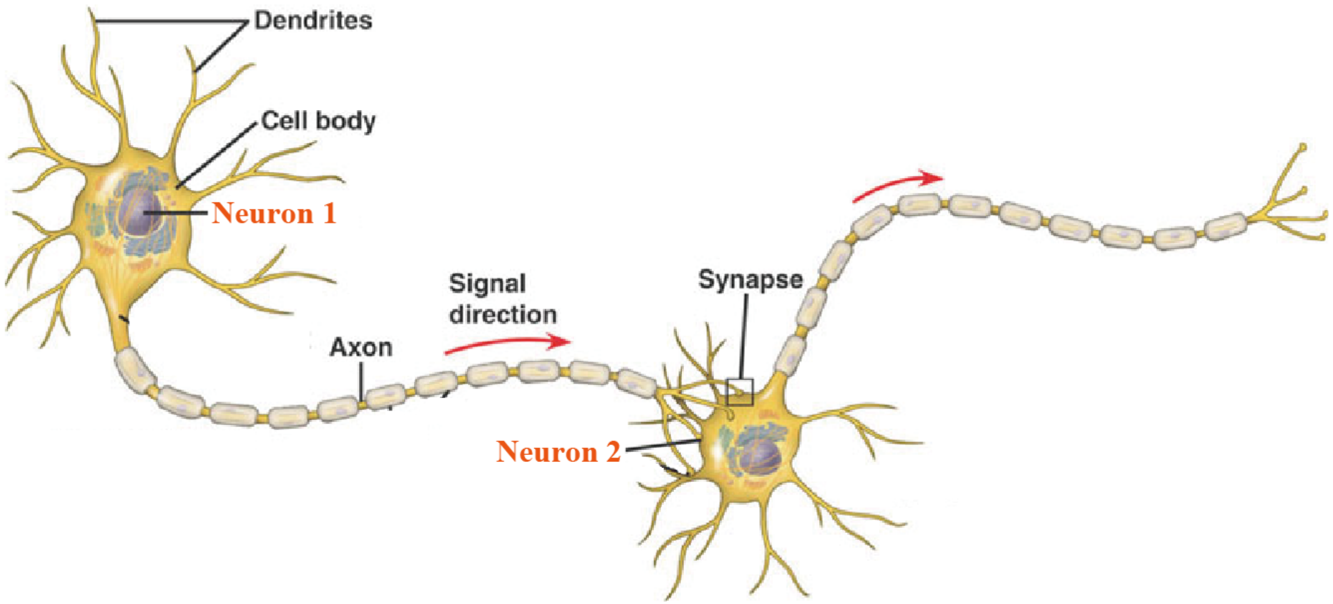
In Perceptron: like MP Neuron, the Perceptron separates the input space into two halves. However, all inputs producing 1 lie on one side, and those producing 0 lie on the other side.
===> A single perceptron can still **only used to implement linearly separable functions**, but not for XOR-like function.

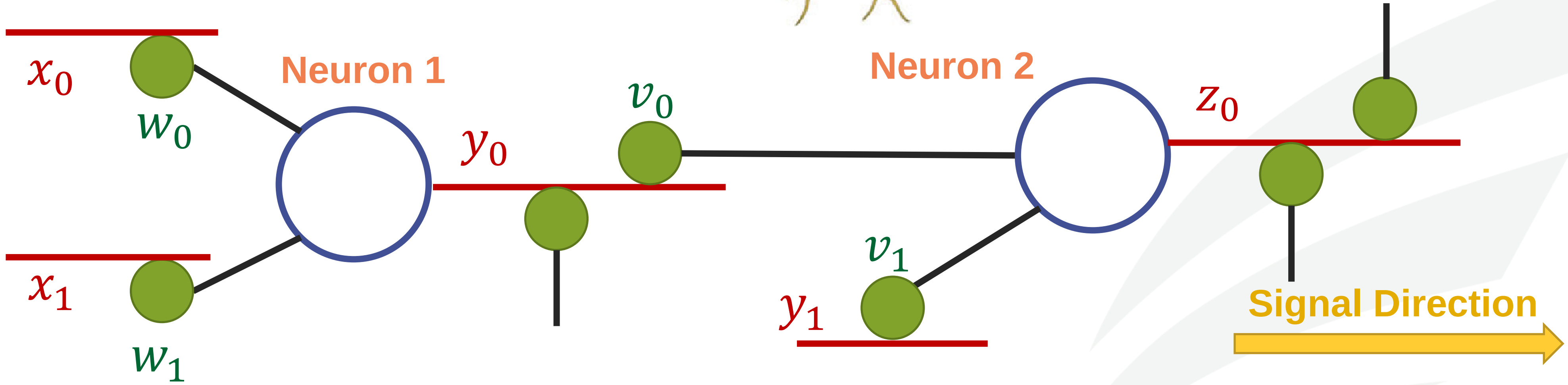
Artificial Neuron Design

- **Idealized neuron models**
  - Idealization removes complicated details that are not essential for understanding the main principles.
  - It allows us to apply mathematics and to make analogies.
- **Break the limitations on MP Neuron**
  - What about non-boolean inputs (say, real number)? ✔
  - What if we want to assign more weight (importance) to some inputs? ✔
  - What about functions which are not linearly separable ? ❓ **=> MLP**
  - Do we always need to hand code the threshold? ❓ **=> Training**

Multi-Layer Perceptron (MLP)

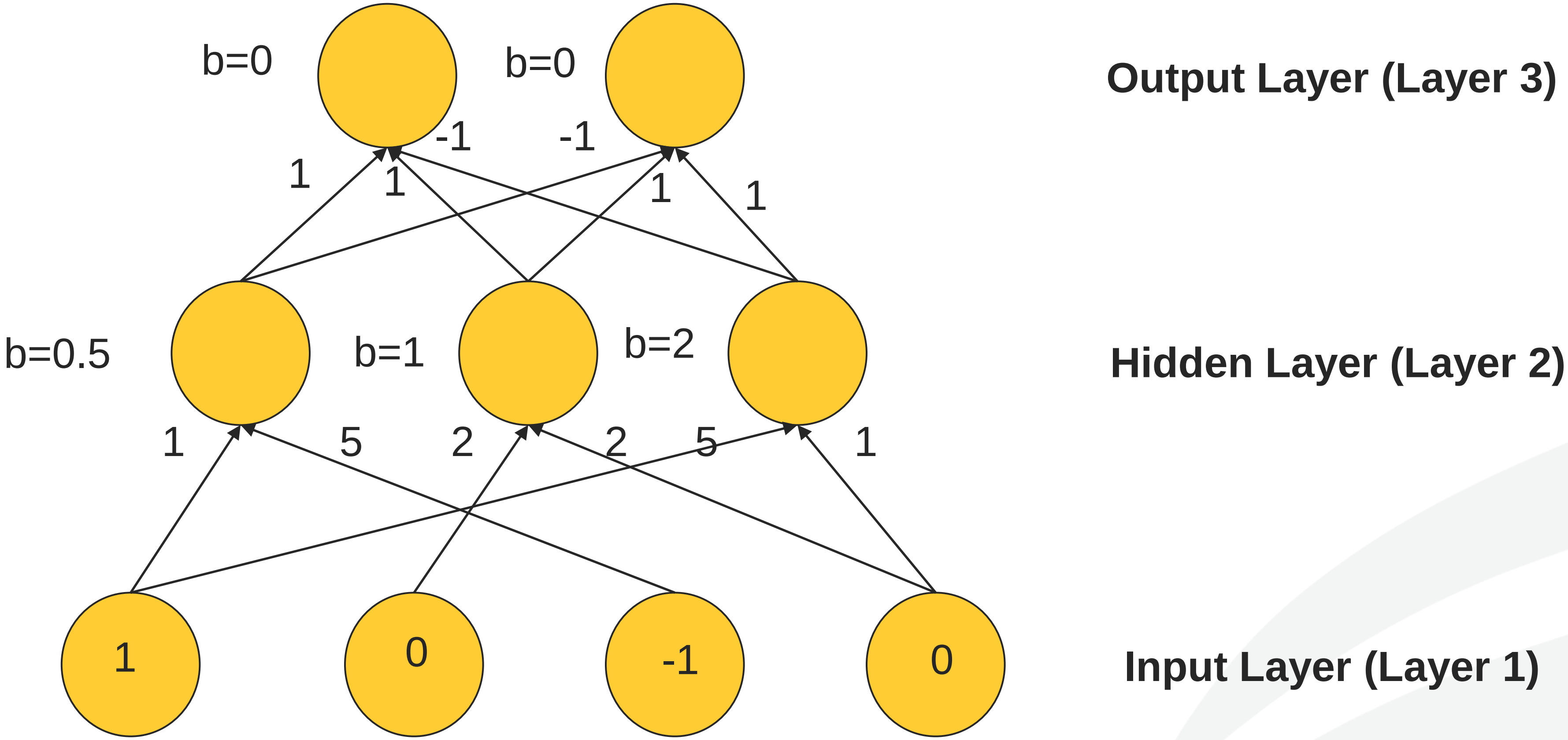
Connect two neurons





Multi-Layer Perceptron (MLP)

Connect more neurons and more layers



Lab 1: Implementing XOR using MLP on Google Colab

Assignments and Related Documents:

- https://jqub.github.io/2021/09/01/ML4Emb/

Due Date: This Friday by 1 PM

- Please take this chance to evaluate the required programming background and the required bandwidth to decide whether keep or drop this course.

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