# Introduction to course "Efficient Deep Learning"

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# What is AI?

## AI

- **Intelligence**: ability to **extract knowledge** from observations
- This knowledge is used to **solve tasks in different contexts and environments**

### Memorizing (explicit)

- Memorize algorithms
- 20th century preferred methodology
- **Pros:** explicit control
- **Cons:** requires explicit solutions

**Not AI**

### Generalization (implicit)

- Infer process from observations
- Guessing game
- **Pros:** universally applicable
- **Cons:** found solution might not be right

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# Machine learning and deep learning

## Machine learning

- Supervised: Infer a function from inputs/outputs

## Difficulties

- Ill-posed problem (infinity of potential solutions)
- Main approach: seek for particular solutions

## Deep Learning

- Express solutions as assembly of atomic functions called layers
  - Compositional approach
- Tune all atomic functions altogether
  - End-to-end learning
- Optimize using stochastic gradient descent variants
  - Differentiable algorithmic

**Ambition: become the new informatics**

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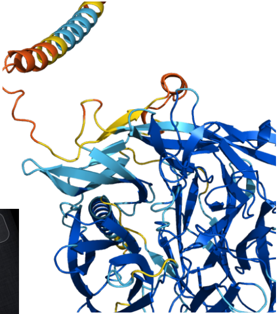
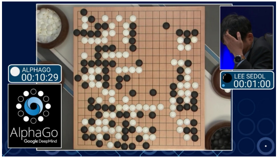
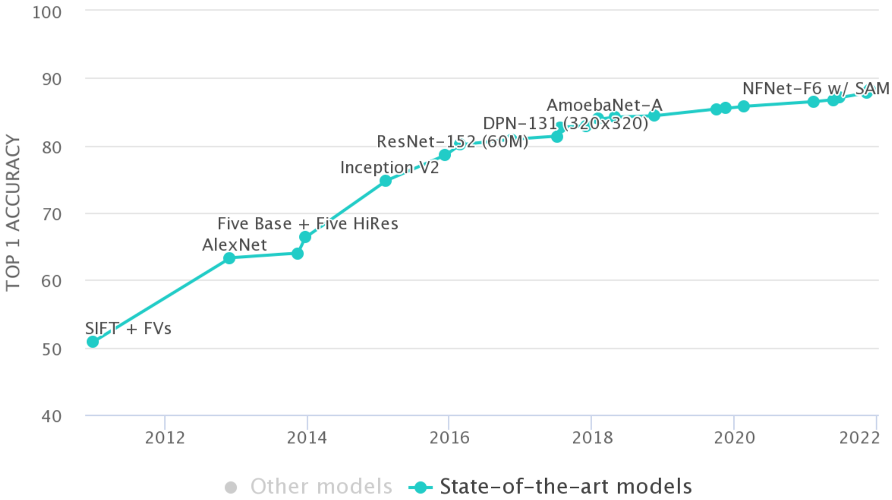
# Main results

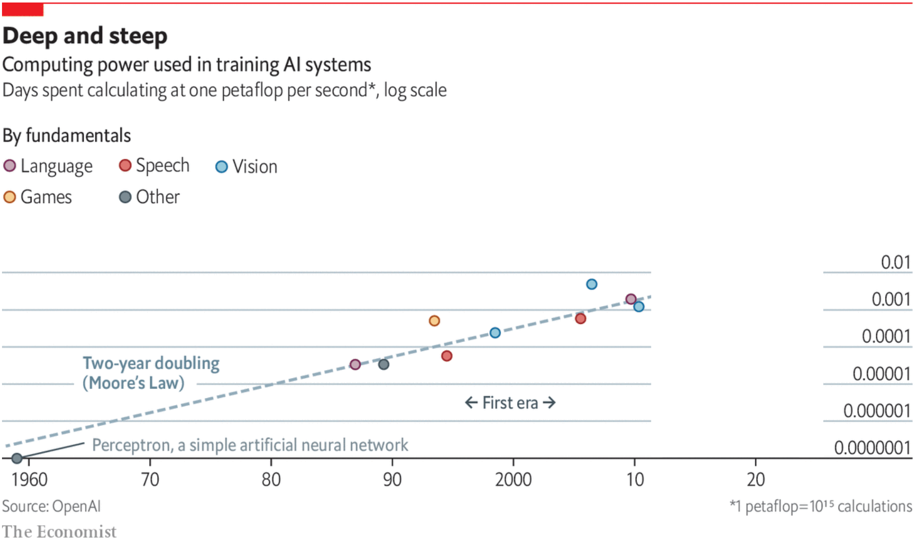


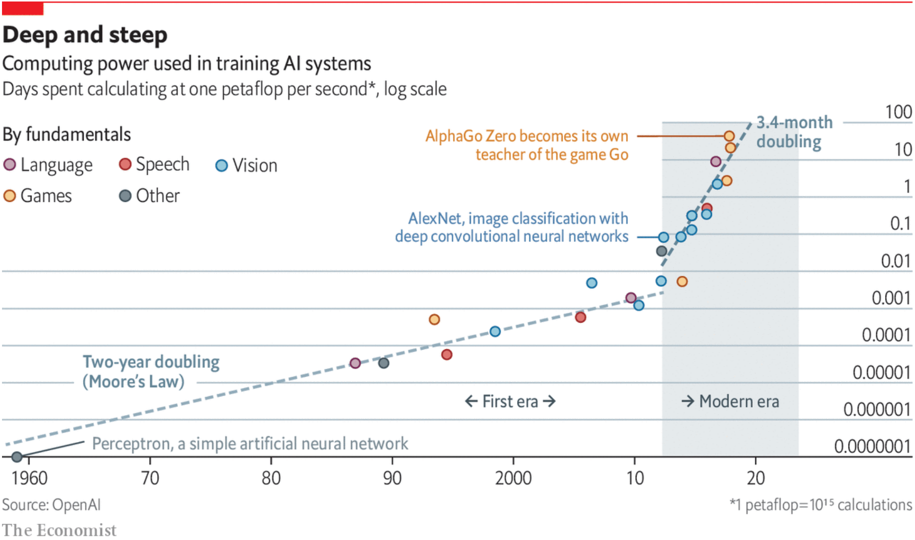

# Example : Image Classification



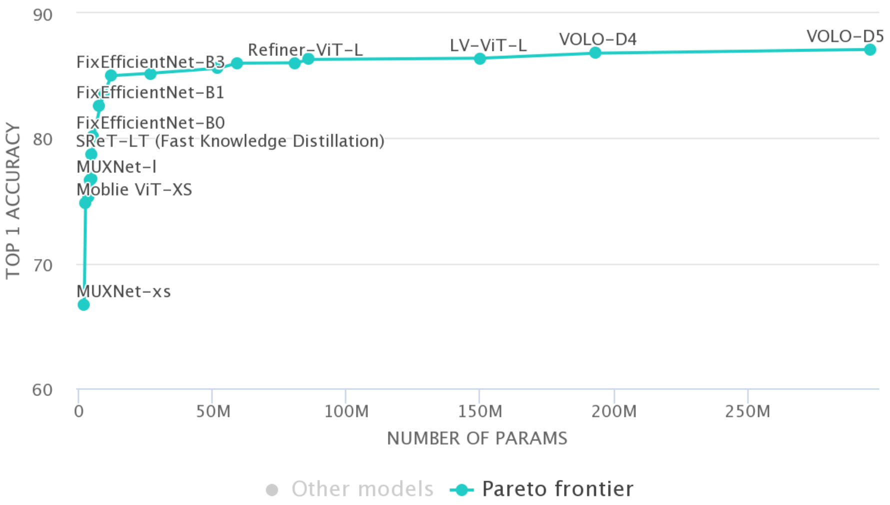

source : https://paperswithcode.com/sota/image-classification-on-imagenet


Deep and steep
Computing power used in training AI systems
Days spent calculating at one petaflop per second*, log scale
By fundamentals
Language
Speech
Vision
Games
Other
0.01
0.001
0.0001
0.00001
0.000001
0.0000001
Two-year doubling
(Moore's Law)
← First era →
Perceptron, a simple artificial neural network
1960
70
80
90
2000
10
20
Source: OpenAI
*1 petaflop=10^15 calculations
The Economist

# Limitation : computations



# Number of parameters of Image Classification DL

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# Making deep learning more efficient

## Why ?

- AI applications on Embedded system / Edge devices
- "Low-tech" AI with limited ressources, no cloud computing

## Problems

- Power consumption of training and inference
- Memory requirements
- Computational power requirements
- Latency

## How ?

- Reduce the number of overall parameters
- Reduce the number of computations needed
- Research on more efficient learning mechanisms

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# Efficient Deep Learning Challenges

## Examples of challenges

- Micronet at NeurIPS 2019
- Low Power Computer Vision (since 2015)
- DCASE Task 1 challenges 2020 and 2021

# MicroNet Challenge

Hosted at NeurIPS 2019

Leaderboard | Overview | Scoring & Submission

## Announcements

1. Join the MicroNet Challenge Google Group to chat with other competitors (link)!

## Overview

Contestants will compete to build the most efficient model that solves the target task to the specified quality level. The competition is focused on efficient inference, and uses a theoretical metric rather than measured inference speed to score entries. We hope that this encourages a mix of submissions that are useful on today's hardware and that will also guide the direction of new hardware development.

source : `micronet-challenge.github.io`

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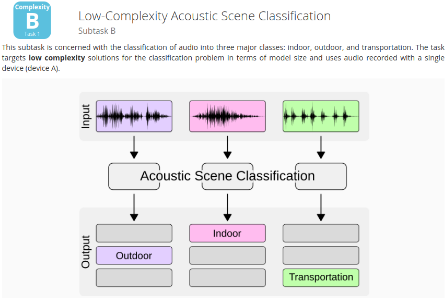

*Figure 1: Overview of acoustic scene classification system.*

source : dcase.community

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| | Submission information | | Evaluation dataset | | | Acoustic model | | | | System |
|---|---|---|---|---|---|---|---|---|---|---|
| Rank | Submission label | Technical Report | Official system rank | Accuracy | Logloss | Parameters | Non-zero parameters | Sparsity | Size (KB) * | Complexity management |
| 1 | Koutini_CPJKU_task1b_2 | | 1 | 96.5 % | 0.101 | 345k | 247k | 0,284 | 483.5 | pruning, float16 |
| 2 | Koutini_CPJKU_task1b_4 | | 2 | 96.2 % | 0.105 | 556k | 249k | 0,552 | 487.1 | float16, smaller width/depth |
| 3 | Hu_GT_task1b_3 | | 3 | 96.0 % | 0.122 | 122k | 122k | 0 | 490.0 | int8, quantization |
| 4 | McDonnell_USA_task1b_3 | | 4 | 95.9 % | 0.117 | 3M | 3M | 0 | 486.7 | 1-bit quantization |
| 5 | Hu_GT_task1b_1 | | 7 | 95.8 % | 0.357 | 94k | 94k | 0 | 375.0 | int8, quantization |
| 5 | Hu_GT_task1b_4 | | 5 | 95.8 % | 0.131 | 125k | 125k | 0 | 499.0 | int8, quantization |
| 5 | McDonnell_USA_task1b_4 | | 6 | 95.8 % | 0.119 | 3M | 3M | 0 | 486.7 | 1-bit quantization |
| 6 | Koutini_CPJKU_task1b_3 | | 8 | 95.7 % | 0.113 | 242k | 242k | 0 | 473.8 | float16, smaller width/depth |
| 7 | Hu_GT_task1b_2 | | 10 | 95.5 % | 0.367 | 122k | 122k | 0 | 490.0 | int8, quantization |
| 7 | McDonnell_USA_task1b_2 | | 9 | 95.5 % | 0.118 | 3M | 3M | 0 | 486.7 | 1-bit quantization |

source : dcase.community

# Course organisation

## Sessions

1. Deep Learning Essentials,
2. Quantification,
3. Pruning,
4. Data Augmentation and Self Supervised Learning,
5. Factorization,
6. Distillation,
7. Embedded Software and Hardware for DL.

## Lab Sessions and Challenge

By groups of two, you are given a machine with complete access.

## Sessions schedule

Each session has (roughly) the same structure:

- **Short written eval** about the previous lesson (10 min),
- Short lesson (20 to 40 min),
- Lab Session,
- Project,
- Sessions 2 and 4 include **students' presentations** before the lesson.