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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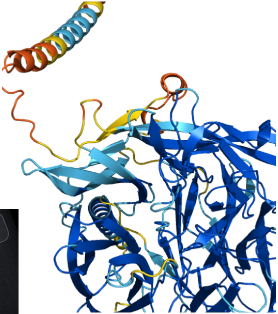
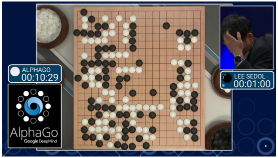
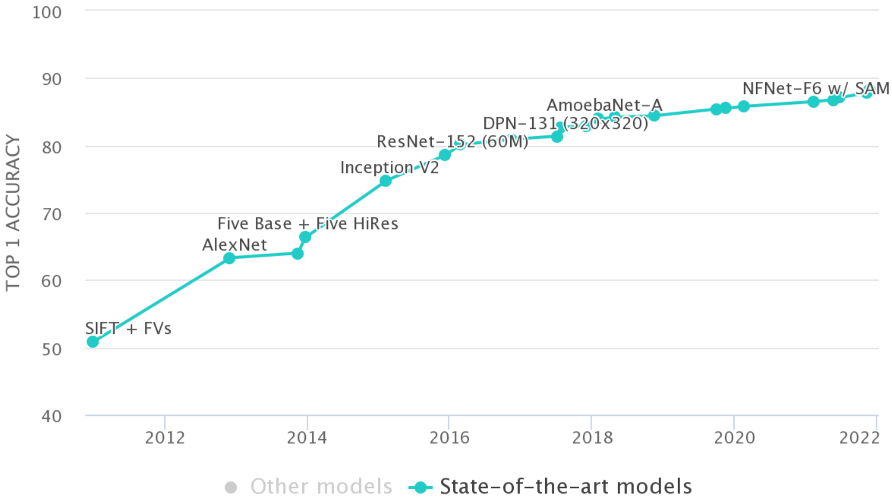




Your AI pair programmer

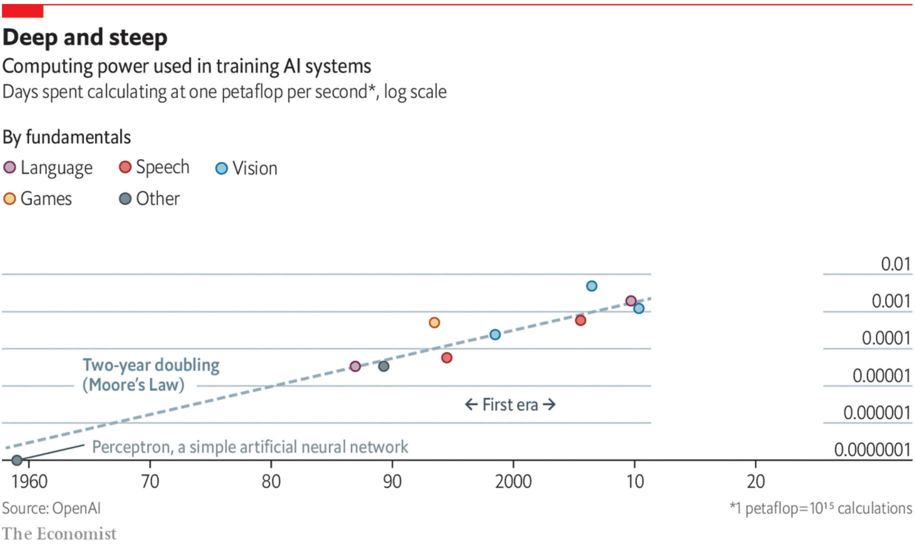
With GitHub Copilot, get suggestions for whole lines or entire functions right inside your editor.

Example : Image Classification



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

Limitation : computations



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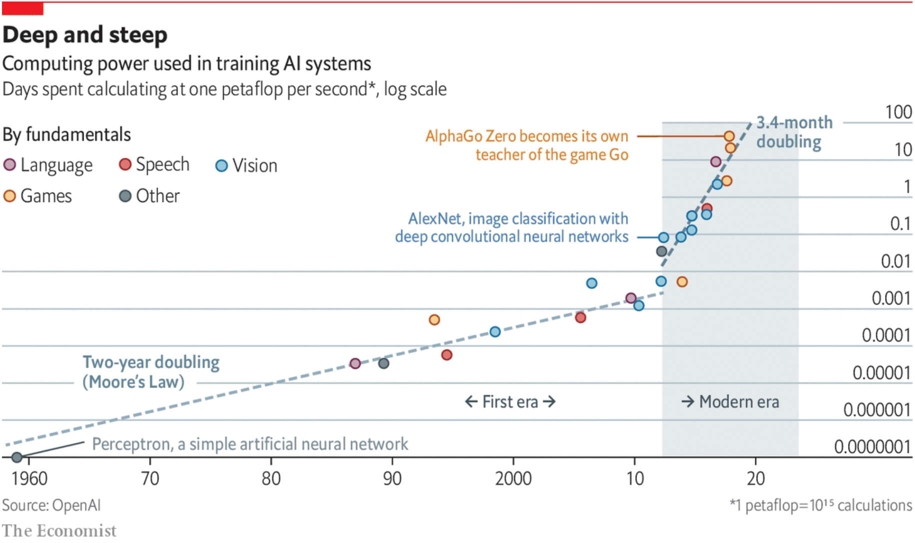
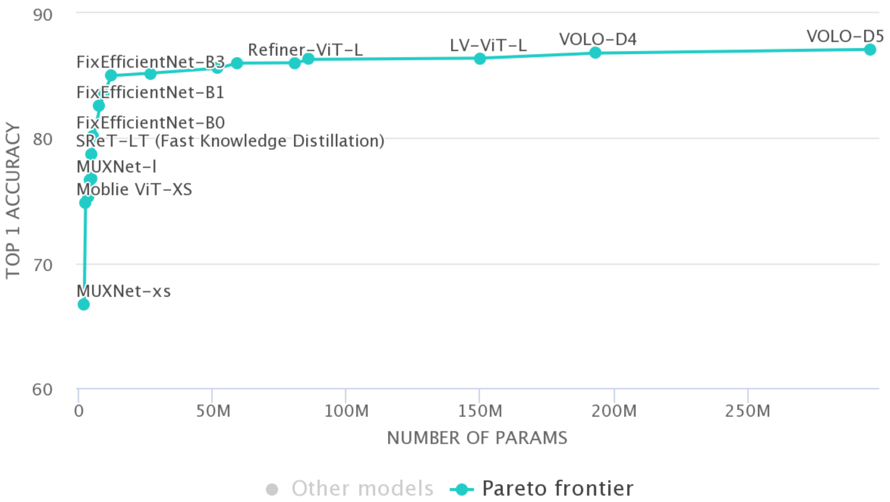


Number of parameters of Image Classification DL



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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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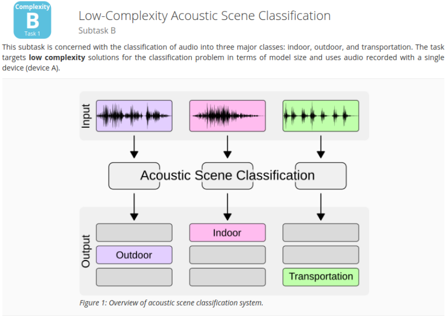

Figure 1: Overview of acoustic scene classification system.

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. Intro Deep Learning,
2. Data Augmentation and Self Supervised Learning,
3. Quantization,
4. Pruning,
5. Factorization,
6. Distillation,
7. Embedded SW / HW for DL.
8. Presentations for challenge.

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 3, 5 and final include **students' presentations**.