Aprendizado Profundo (Deep Learning)

Introduction

Dario Oliveira (dario.oliveira@fgv.br)

The Team

- Instructor: Dário Oliveira (dario.oliveira@fgv.br)
- Tutors:
  - Laura Cue
  - Daliana Torres

Me

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2007 — **BSc Electrical Engineering**
Rio de Janeiro State University

2009 — **MSc Electrical Engineering**
Pontifical Catholic University of Rio de Janeiro
(Instituto Superior Técnico - Portugal)

2013 — **PhD Electrical Engineering**
Pontifical Catholic University of Rio de Janeiro
(Leibniz Universität Hannover - Germany)

2015 — **Postdoctoral Researcher**
University of São Paulo

2016 — **Research Scientist**
General Electric Global Research Center

Research Scientist
IBM Research

2021 — **Research Associate**
University of Wisconsin-Madison

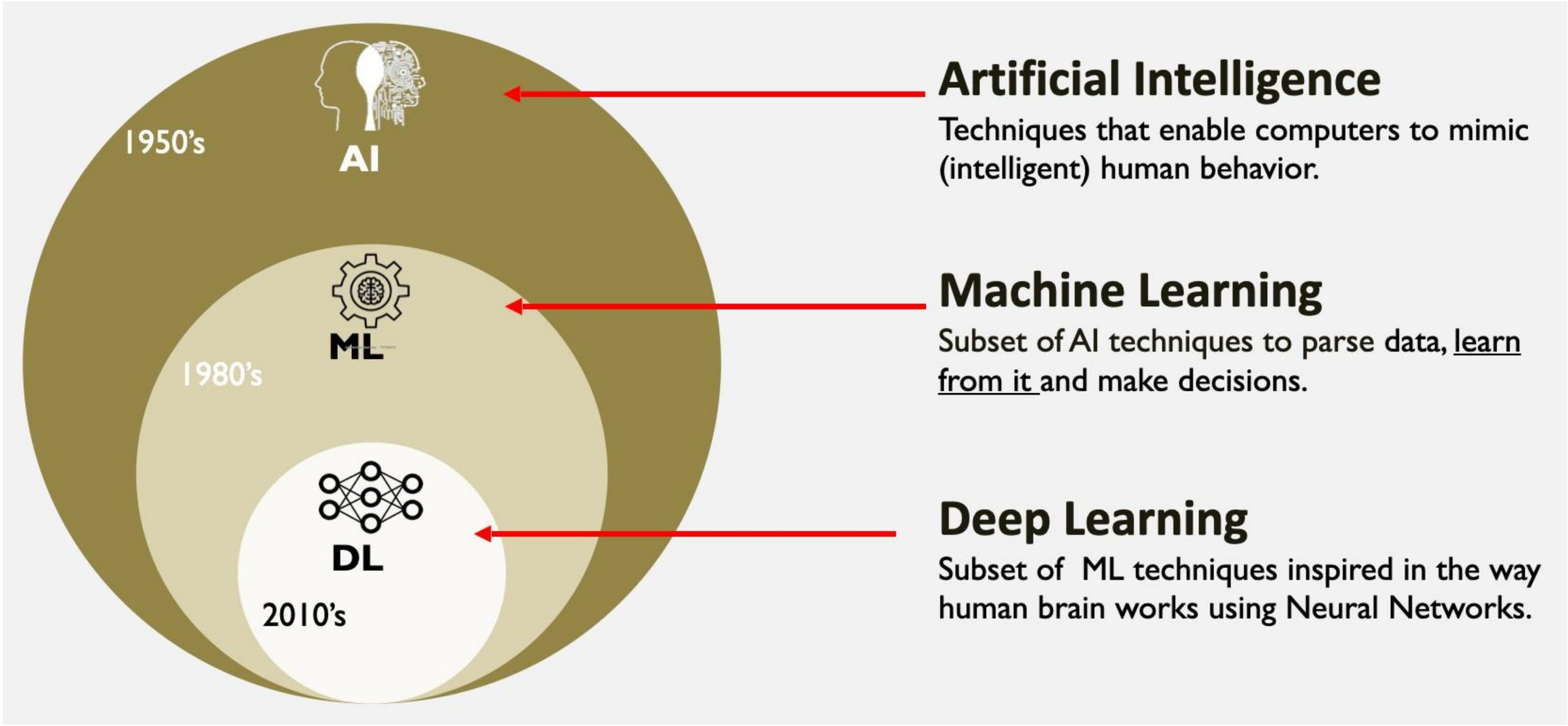
2022 — **Guest Professor**
Technische Universität München

Professor
School of Applied Mathematics - FGV

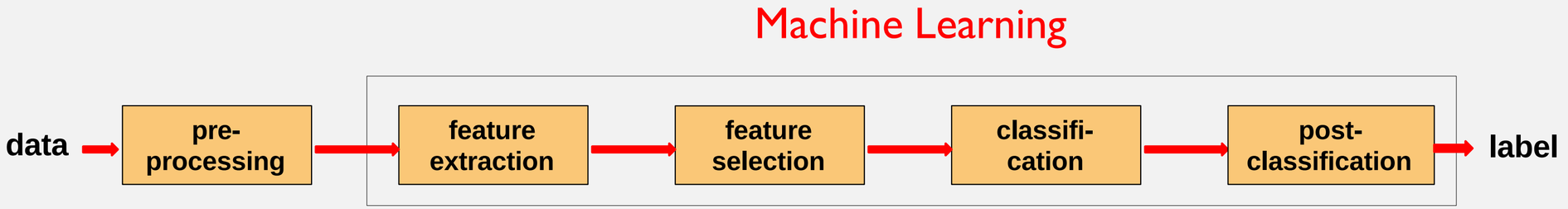
The Class

- How about you?
- Interests on ML/DL?
- Any prior python/colab knowledge?
- Any prior ML/DL knowledge?

Deep Learning

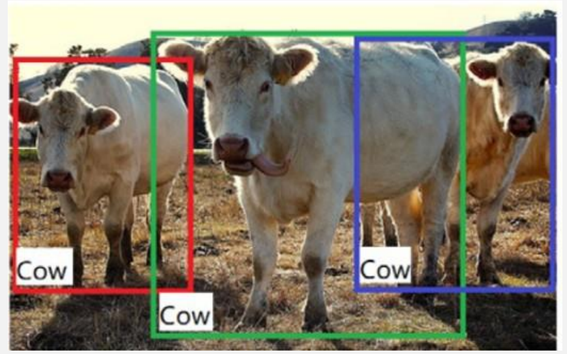


Classical Machine Learning

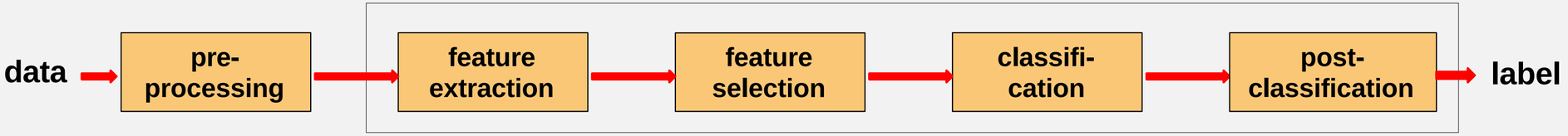


Classical Machine Learning

Detection

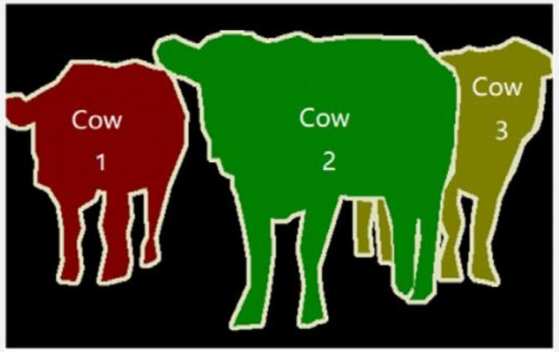


Machine Learning

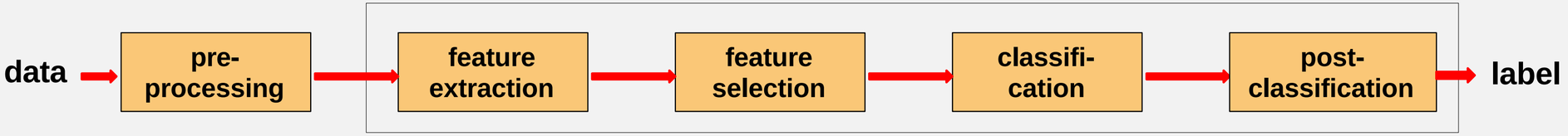


Classical Machine Learning

Segmentation

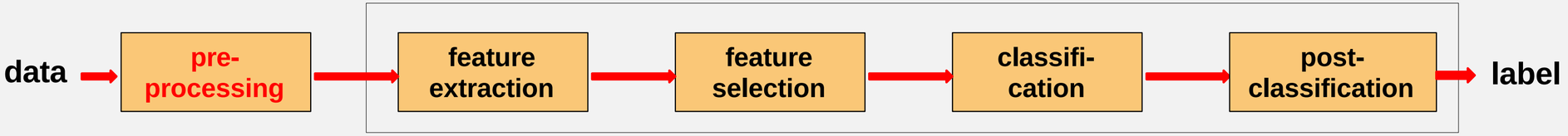


Machine Learning



Classical Machine Learning

Machine Learning

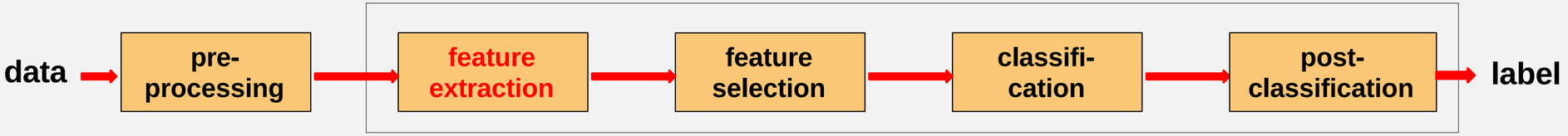


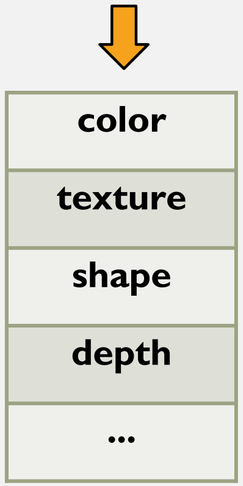
Improves image data towards a common standard quality

Classical Machine Learning

features

Machine Learning





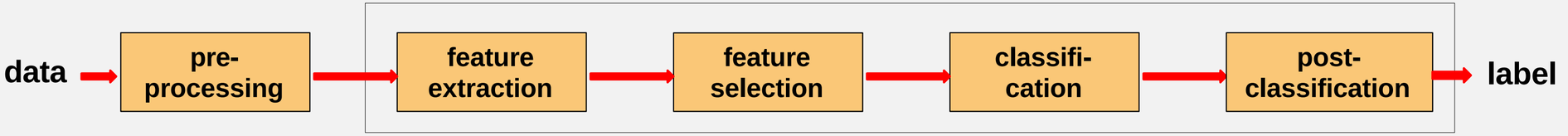
Measures properties (**features**) of data chunks (e.g., pixels, superpixels, regions)

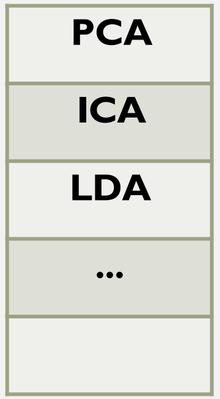
Classical Machine Learning

features

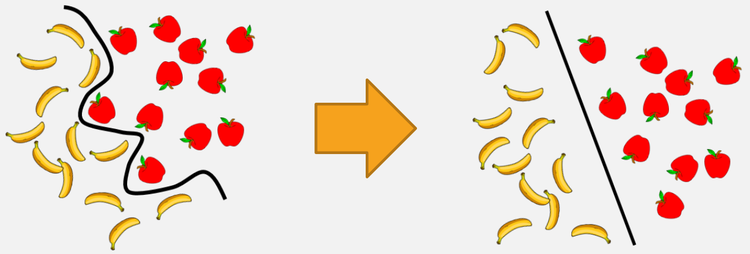
features

Machine Learning

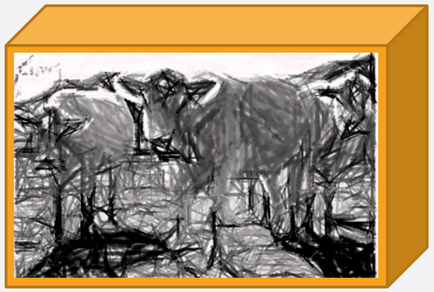




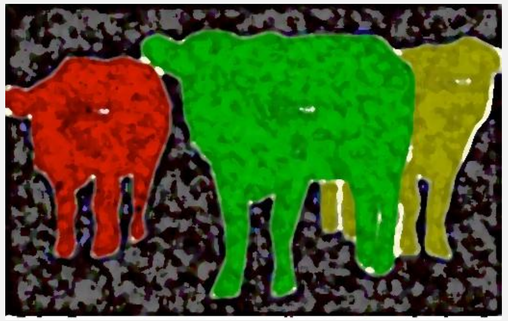
Finds a feature space where samples from different classes are well separable.



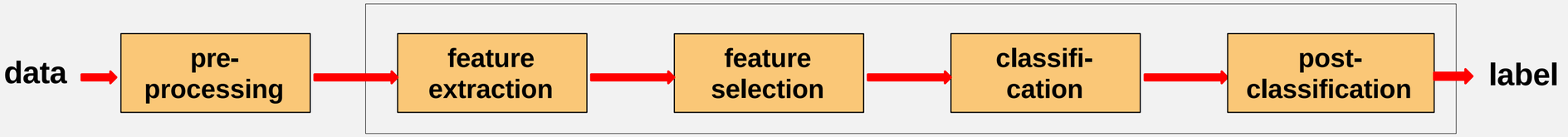
Classical Machine Learning

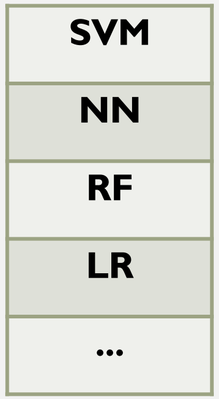


features



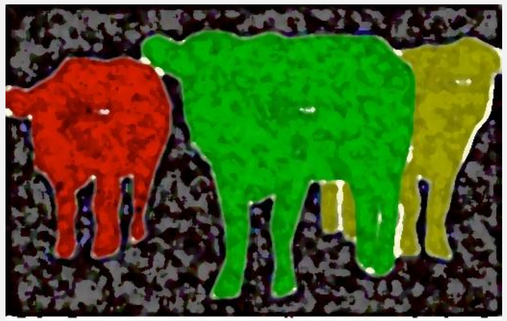
Machine Learning

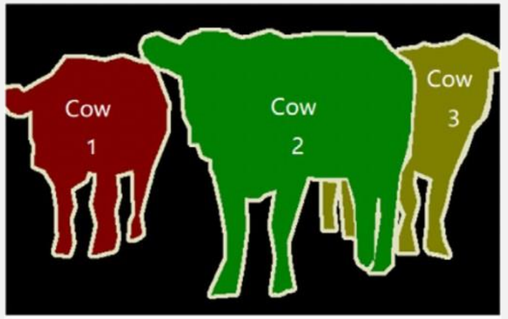




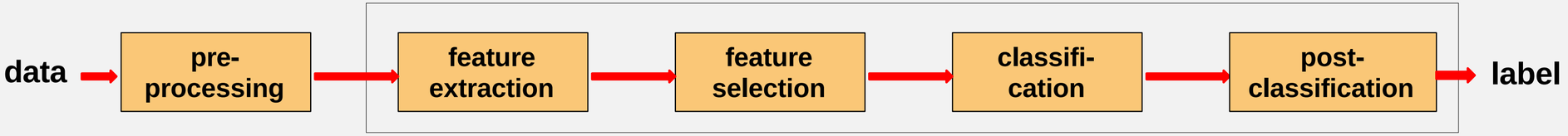
Assigns inputs (data) to output (e.g., classes).

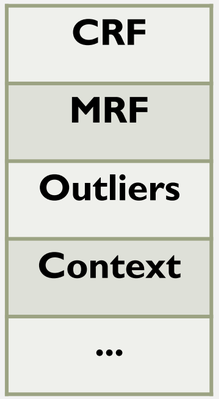
Classical Machine Learning





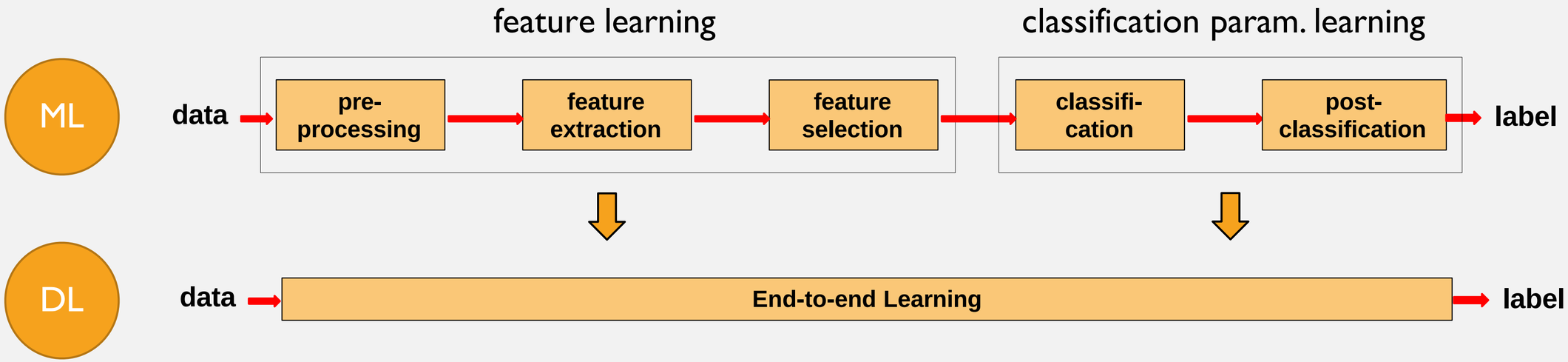
Machine Learning



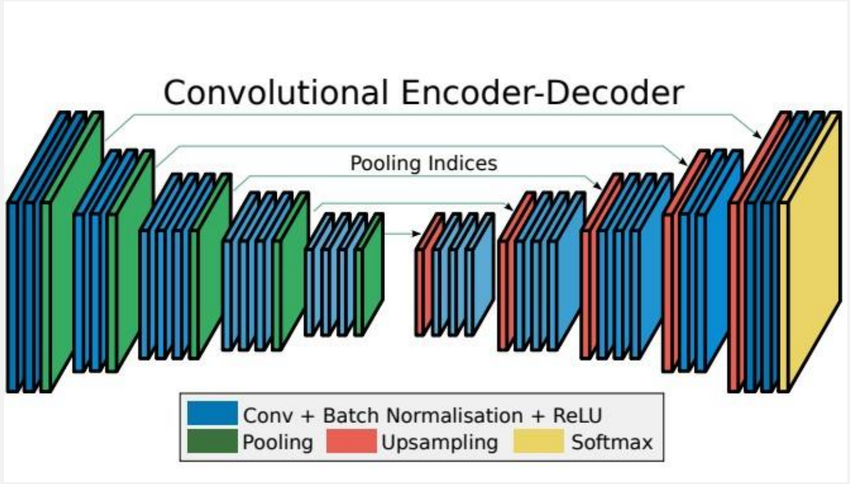


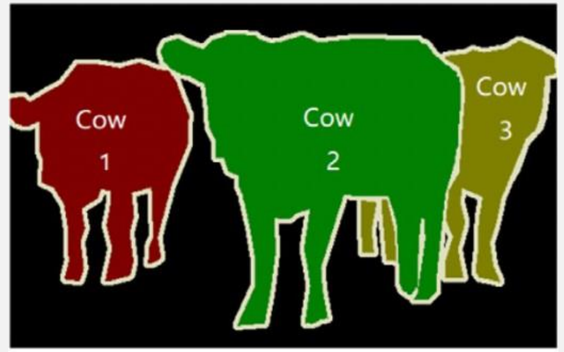
Improves the quality of the classification output.

Classical Machine Learning vs Deep Learning



"End-to-end" refers to automatically learning features and classification parameters jointly (vs. step-by-step) straight from the data.

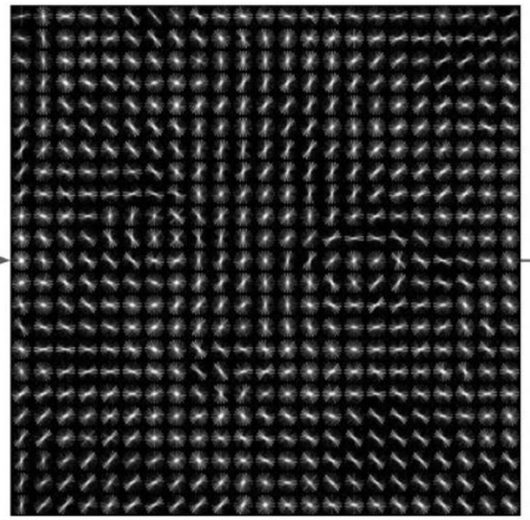




Classical Machine Learning vs Deep Learning

Input image

Preprocessing



Features : HAAR, HOG, SIFT, SURF

Learning Algorithm

SVM, Random Forests, ANN

Label Assignment

Cat or Background

Classical Machine Learning vs Deep Learning

Input image

Awesome magic box

Label Assignment

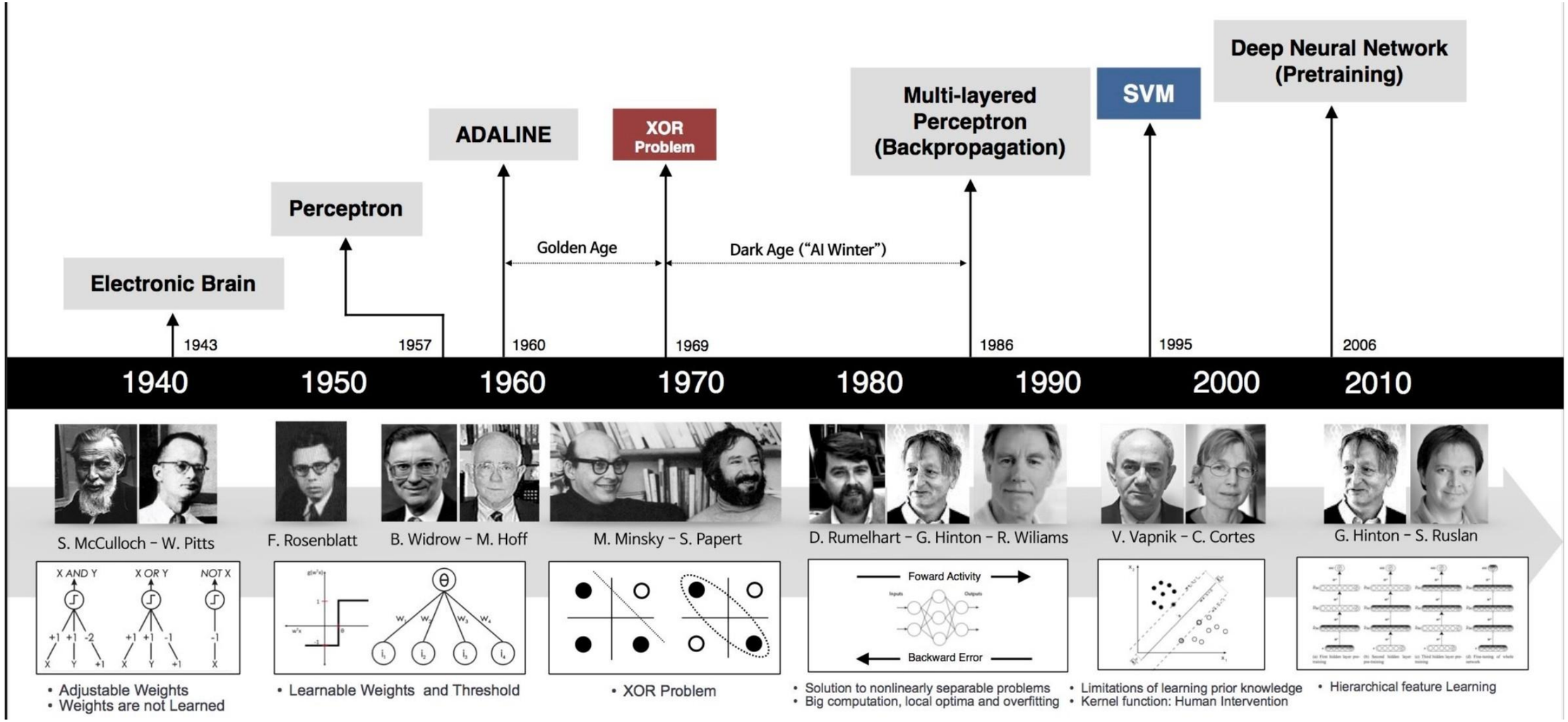
Cat or Background

Open the box

Become magicians

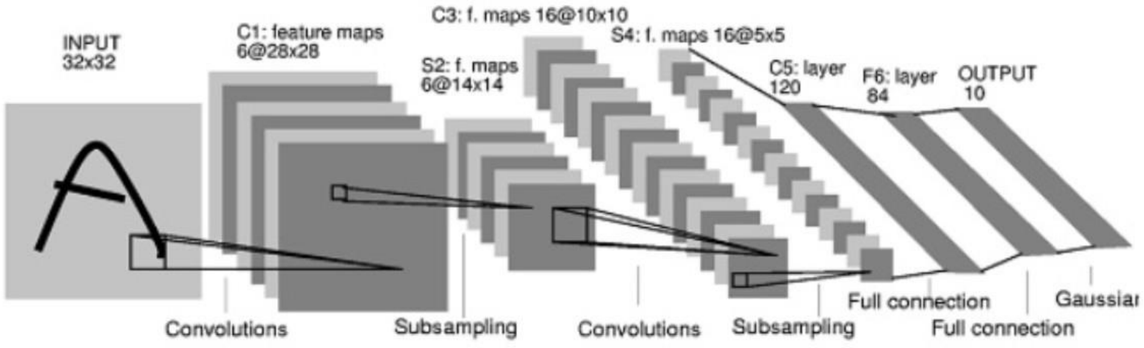
Post 2012

Deep Learning History



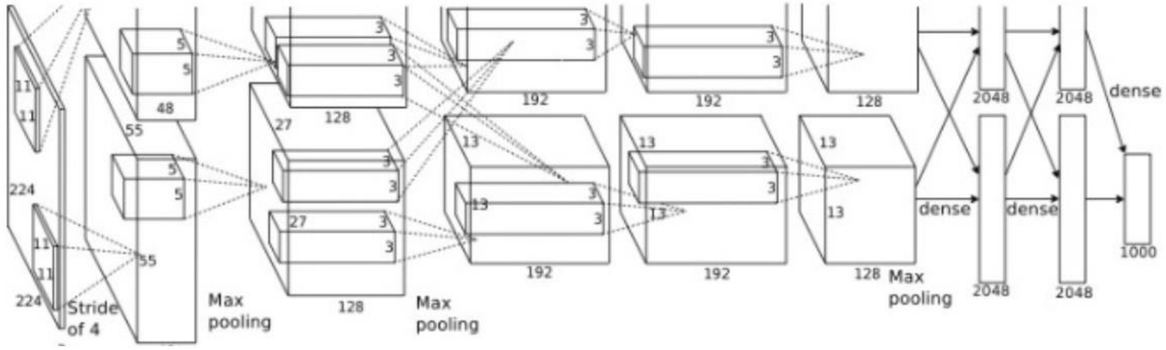
Game Changers

1998
LeCun
et al.



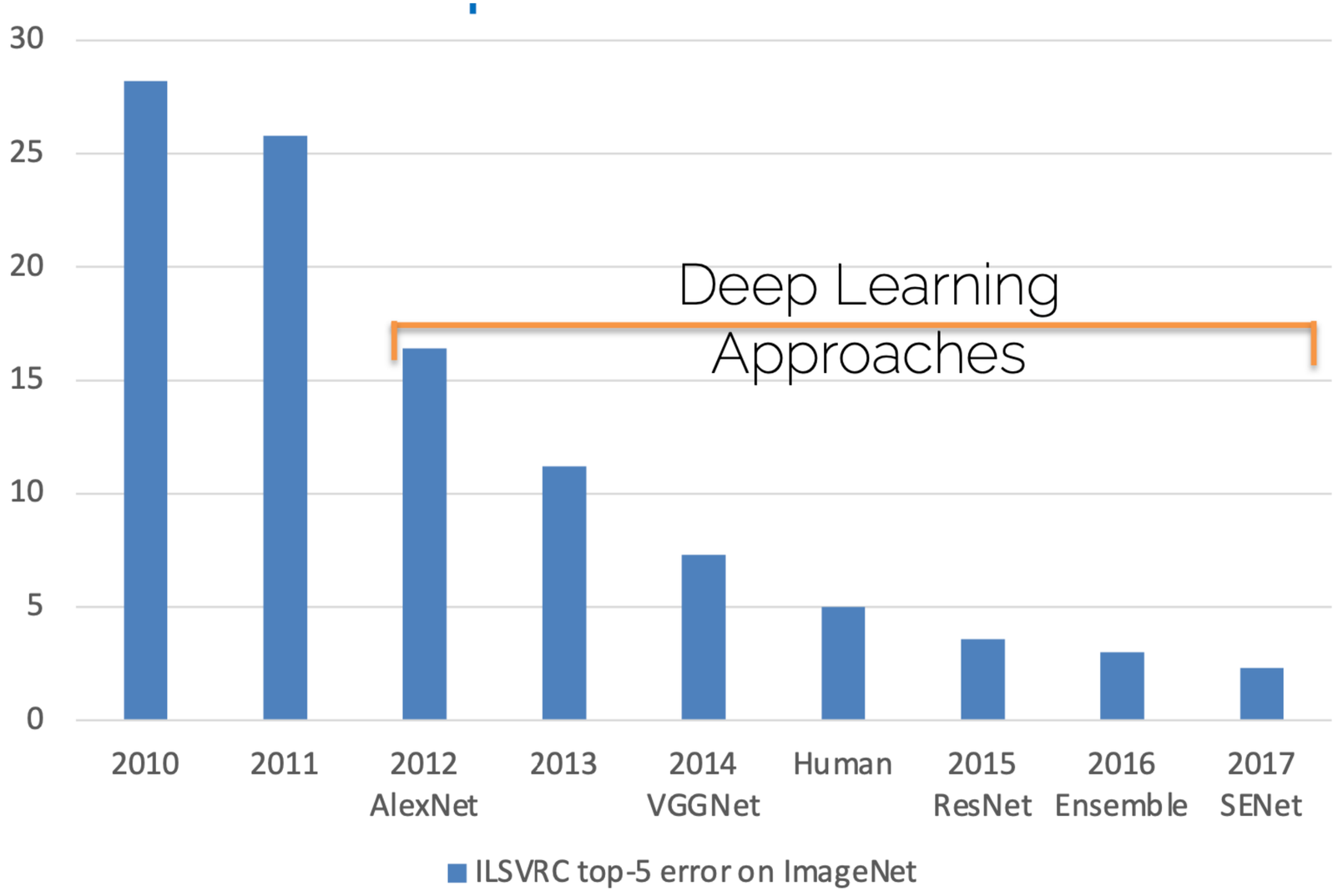
- MNIST digit recognition dataset
- 10^7 pixels used in training

2012
Krizhevsky
et al.



- ImageNet image recognition dataset
- 10^{14} pixels used in training

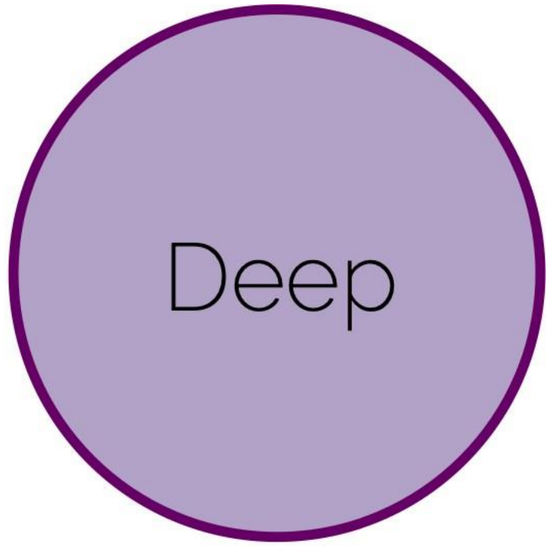
Starting a Deep Learning Revolution



What made that possible?

Models know
where to learn from

Models are
trainable

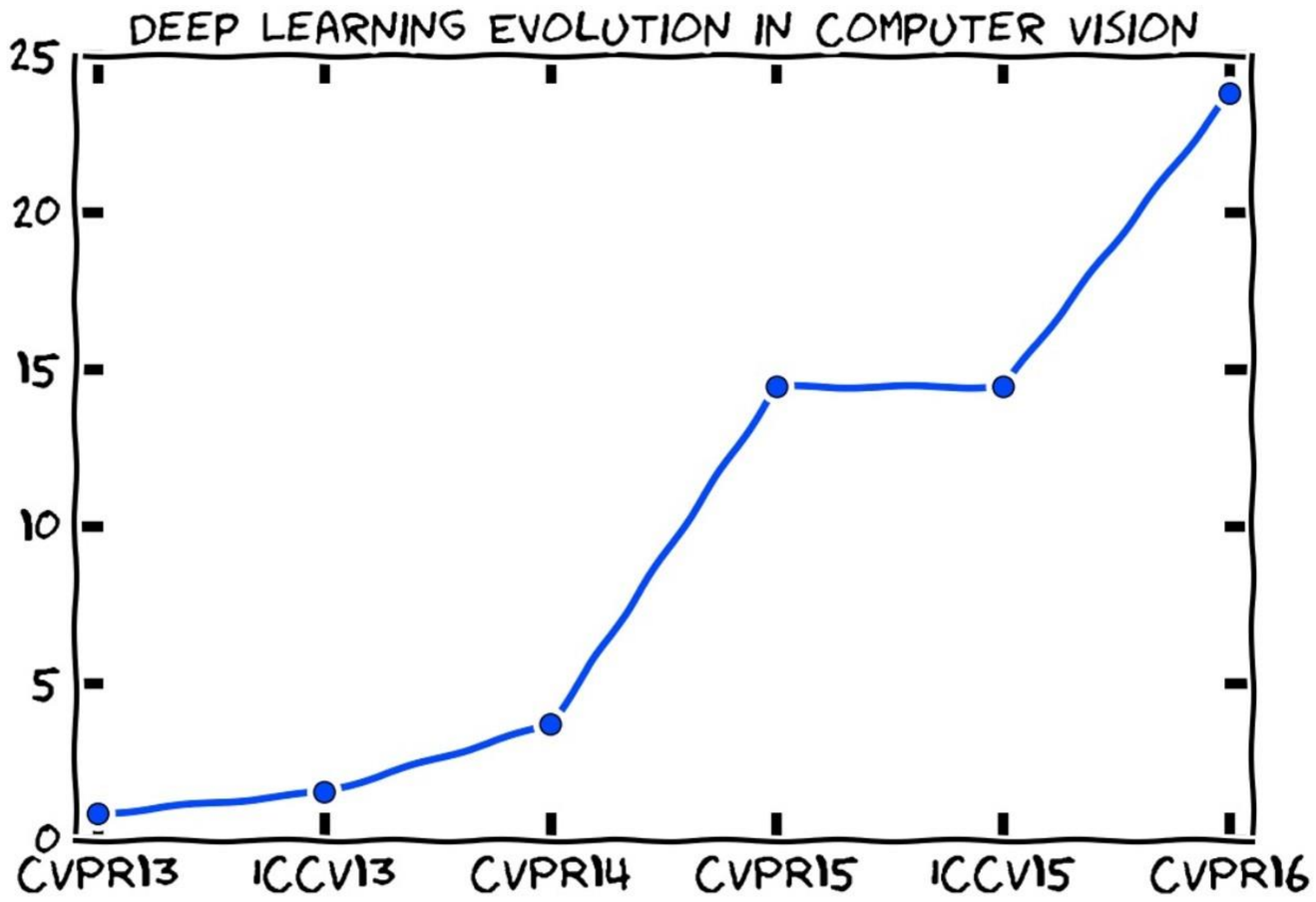


Models are
complex

Deep Learning Recognition

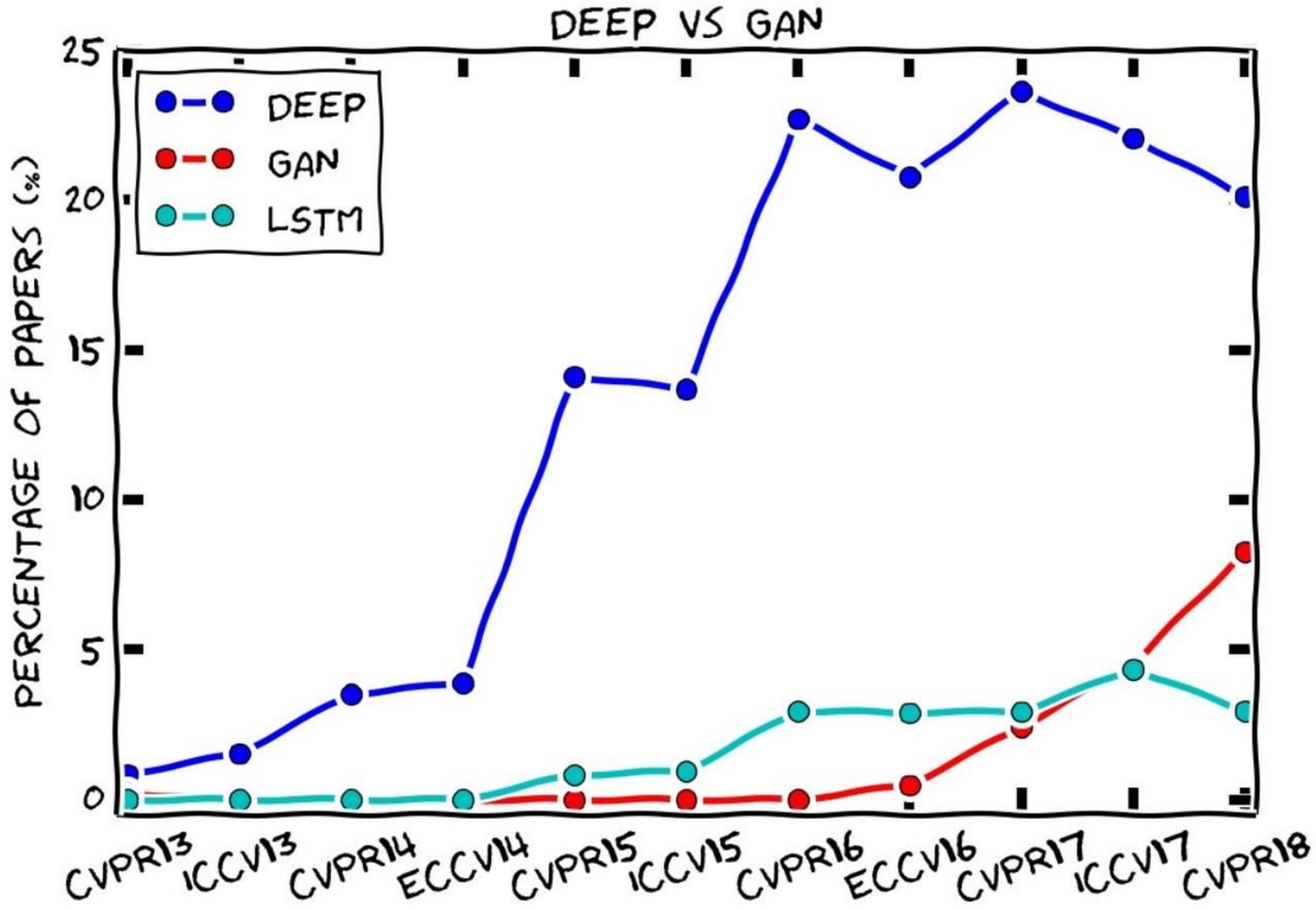
ACM Turing Award 2019 (Nobel Prize of Computing)
Yann LeCun, Geoffrey Hinton, and Yoshua Bengio

Deep Learning (R)evolution



Credits: Dr. Pont-Tuset, ETH Zurich

Deep Learning (R)evolution

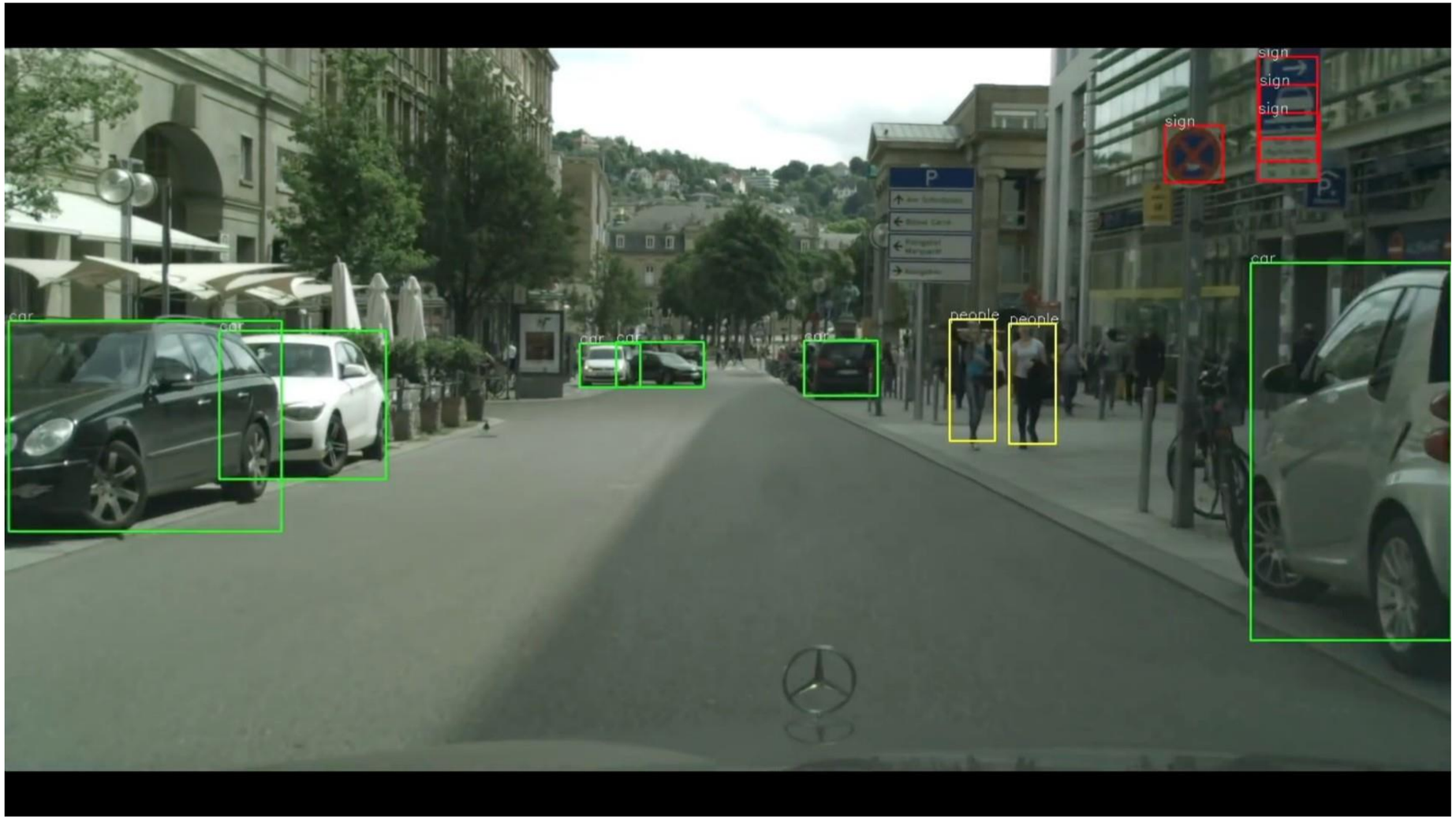


Credits: Dr. Pont-Tuset, ETH Zurich

Deep Learning Today

Object Detection

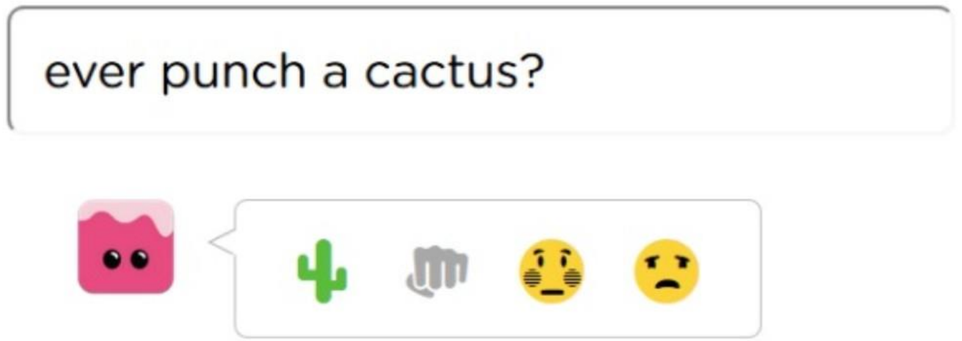
Deep Learning Today



Self-driving cars

Deep Learning Today

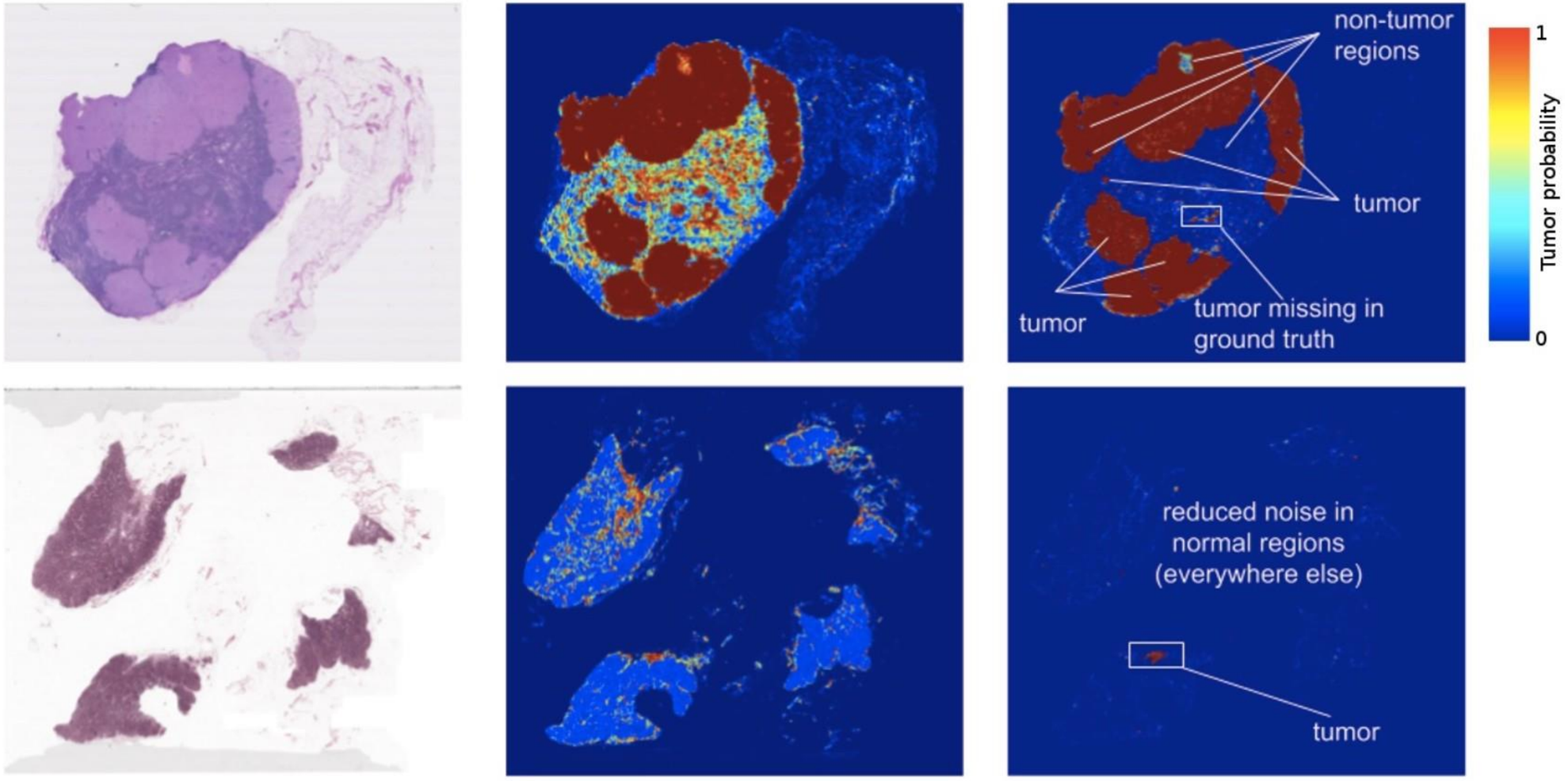
AlphaGo



Emoticon suggestion

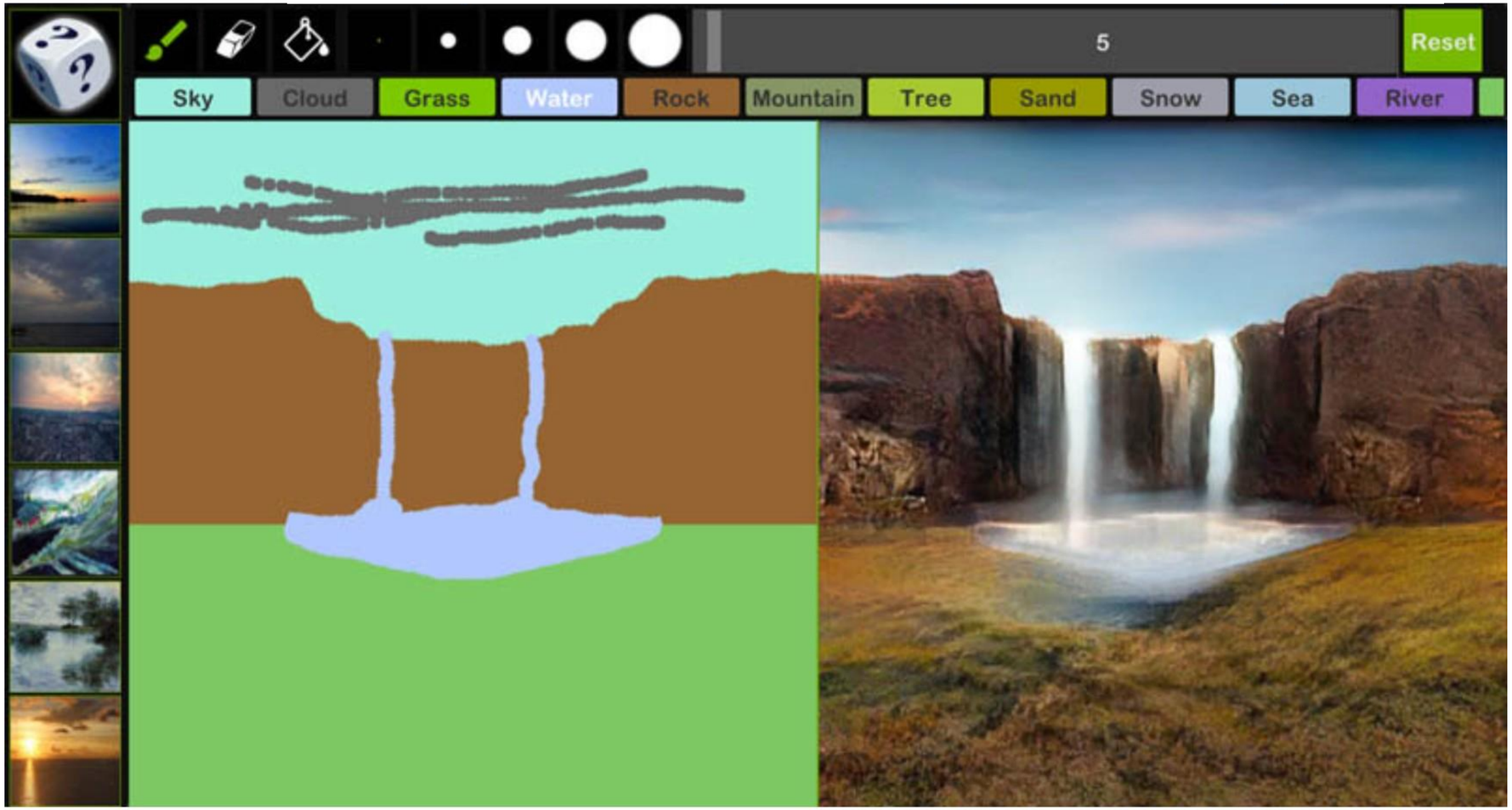
Machine translation

Deep Learning Today



Healthcare, cancer detection

Deep Learning Today



GauGAN – from sketch to image

Deep Learning Today

TEXT DESCRIPTION

An astronaut Teddy bears A bowl of soup

mixing sparkling chemicals as mad scientists shopping for groceries working on new AI research

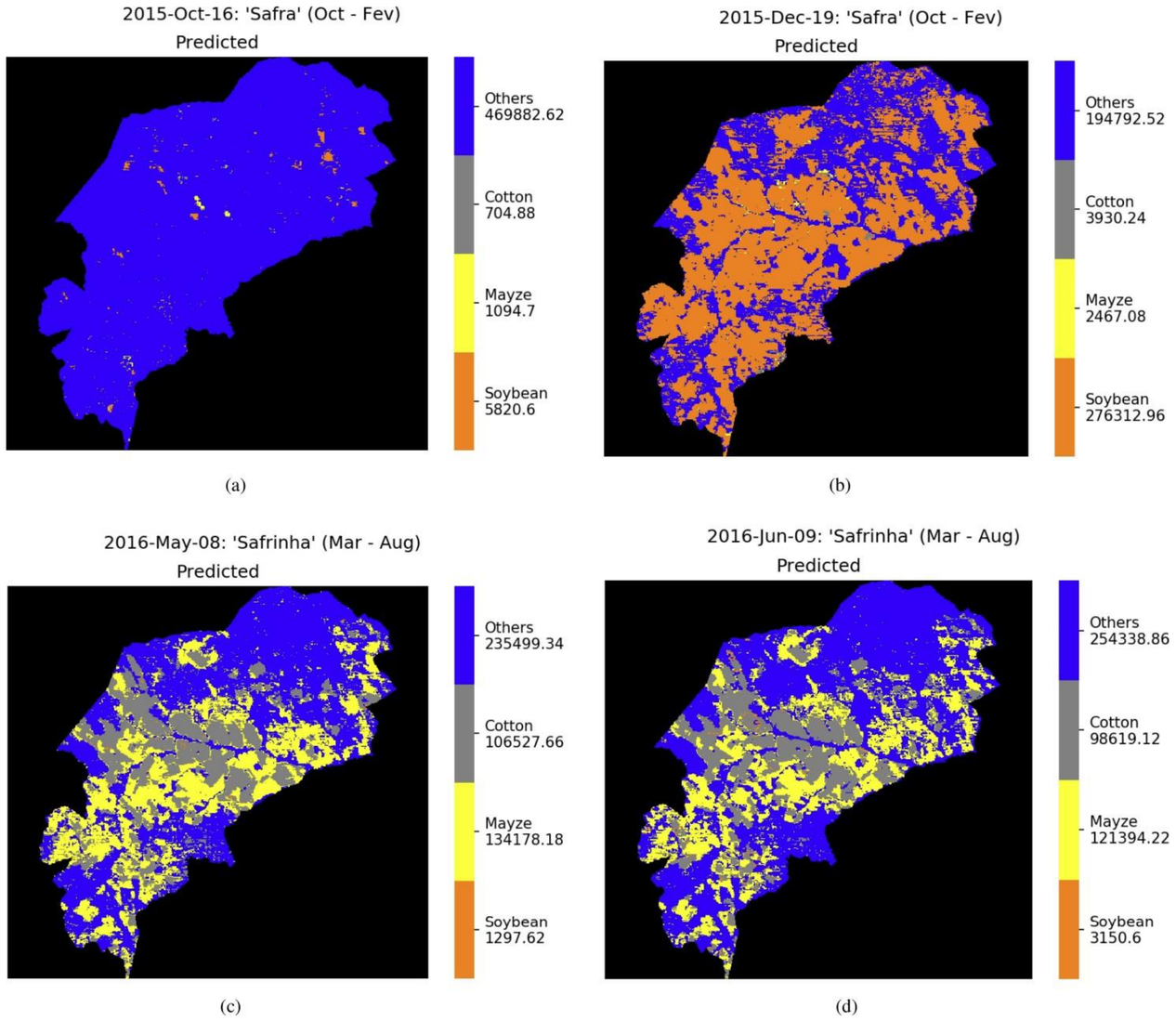
in the style of ukiyo-e as a one-line drawing in ancient Egypt

→

DALL·E 2

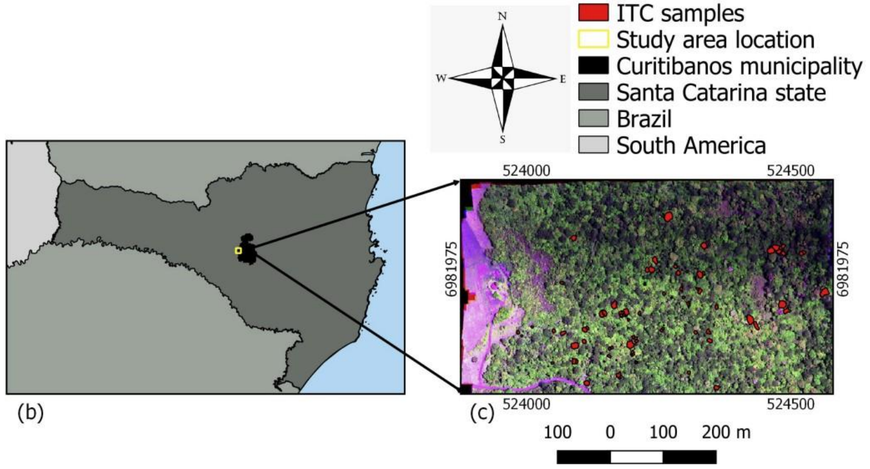
[Dall-E 2] Image generation from text

Deep Learning Today

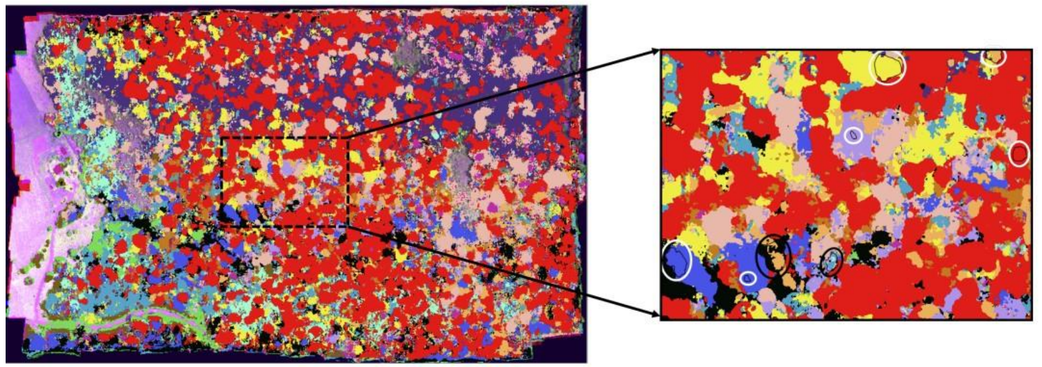


Agricultural Mapping for a Geographic Region

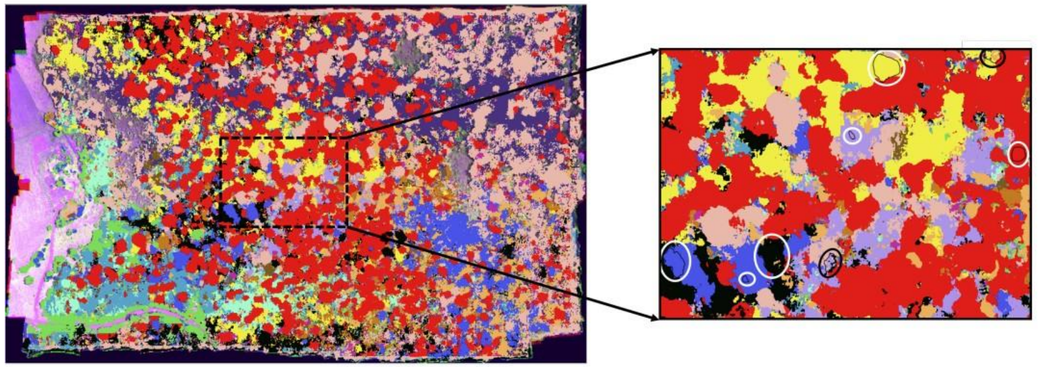
Deep Learning Today



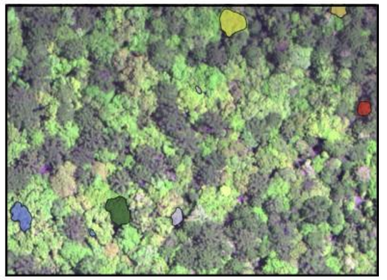
a) STFCsp classification map



b) MTFCsp classification map



c) Orthoimage with labels

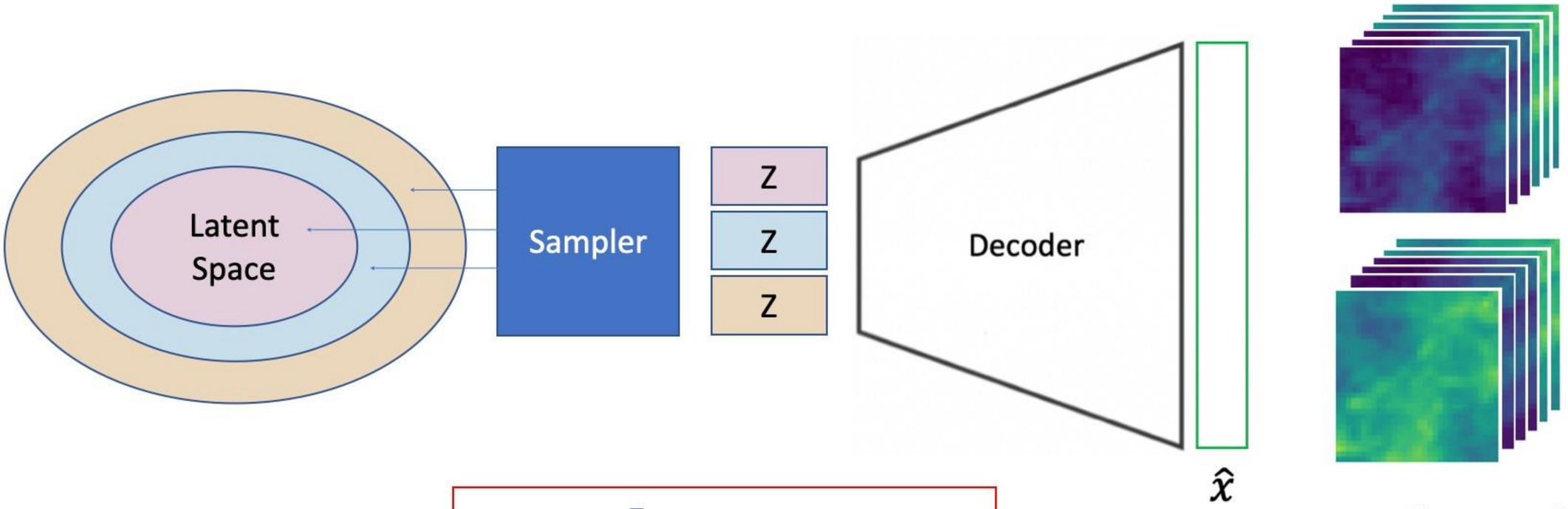


d) Area (ha and %) for the 14 species

	STFCsp	MTFCsp
Luehea	1.41 (5%)	1.62 (6%)
Araucaria	8.95 (34%)	6.60 (25%)
Mimosa	0.67 (3%)	0.83 (3%)
Lithraea	1.21 (5%)	1.31 (5%)
Campomanesia	3.67 (14%)	2.74 (11%)
Cedrela	1.68 (6%)	1.79 (7%)
Cinnamodendron	0.39 (2%)	0.26 (1%)
Cupania	1.53 (6%)	1.00 (4%)
Matayba	1.25 (5%)	2.03 (8%)
Nectandra	0.42 (2%)	0.43 (2%)
Ocotea	2.88 (11%)	6.20 (24%)
Podocarpus	0.83 (3%)	0.67 (3%)
Schinus sp1	0.58 (2%)	0.40 (2%)
Schinus sp2	0.96 (4%)	0.57 (2%)

Multi-task fully convolutional network for tree species mapping in dense forests using small training hyperspectral data, Rosa et al., ISPRS JPRS 2021

Deep Learning Today

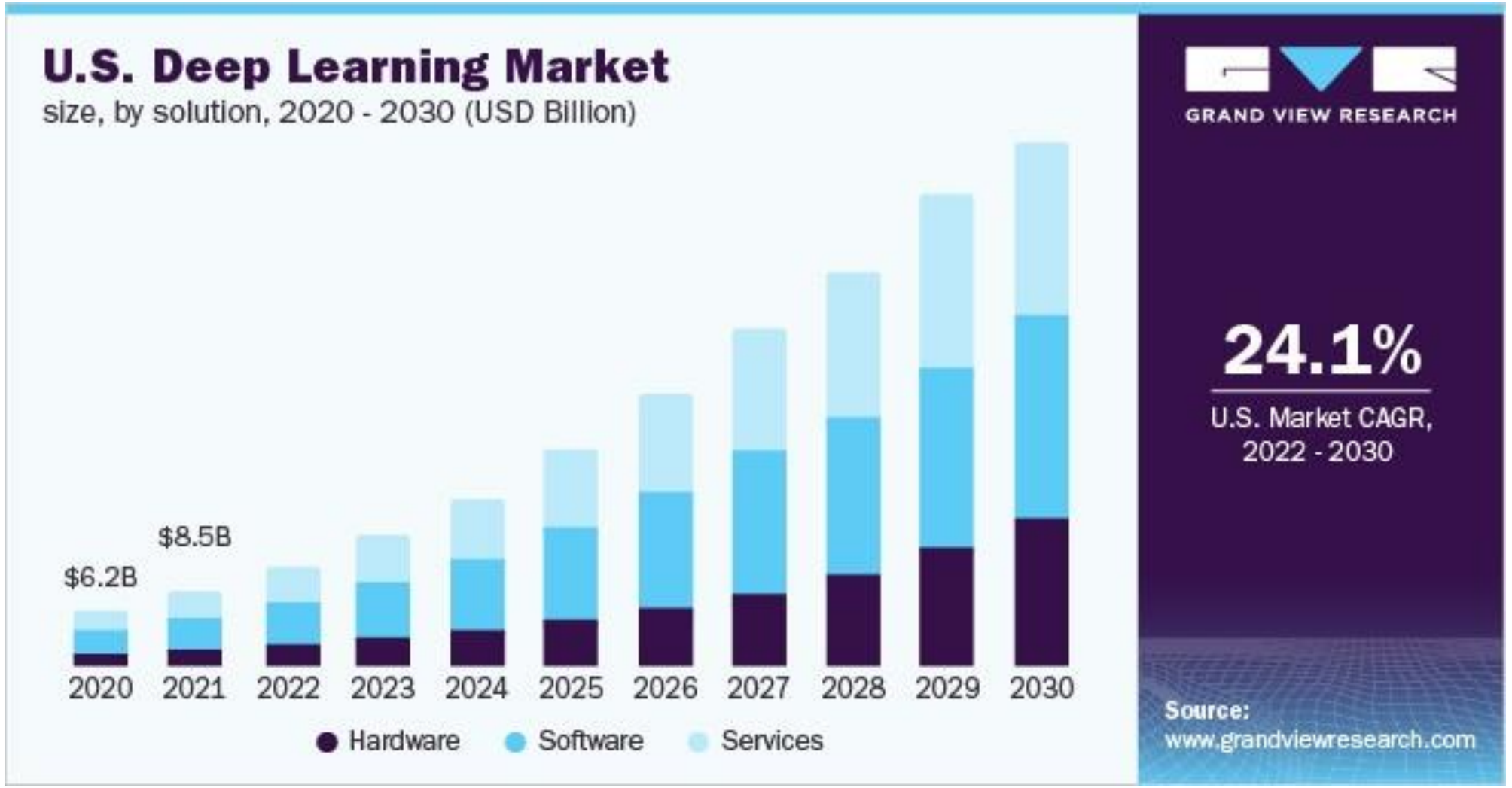


Controlling Weather Field Synthesis

We don not need to define exactly what extreme means!
extreme=rare

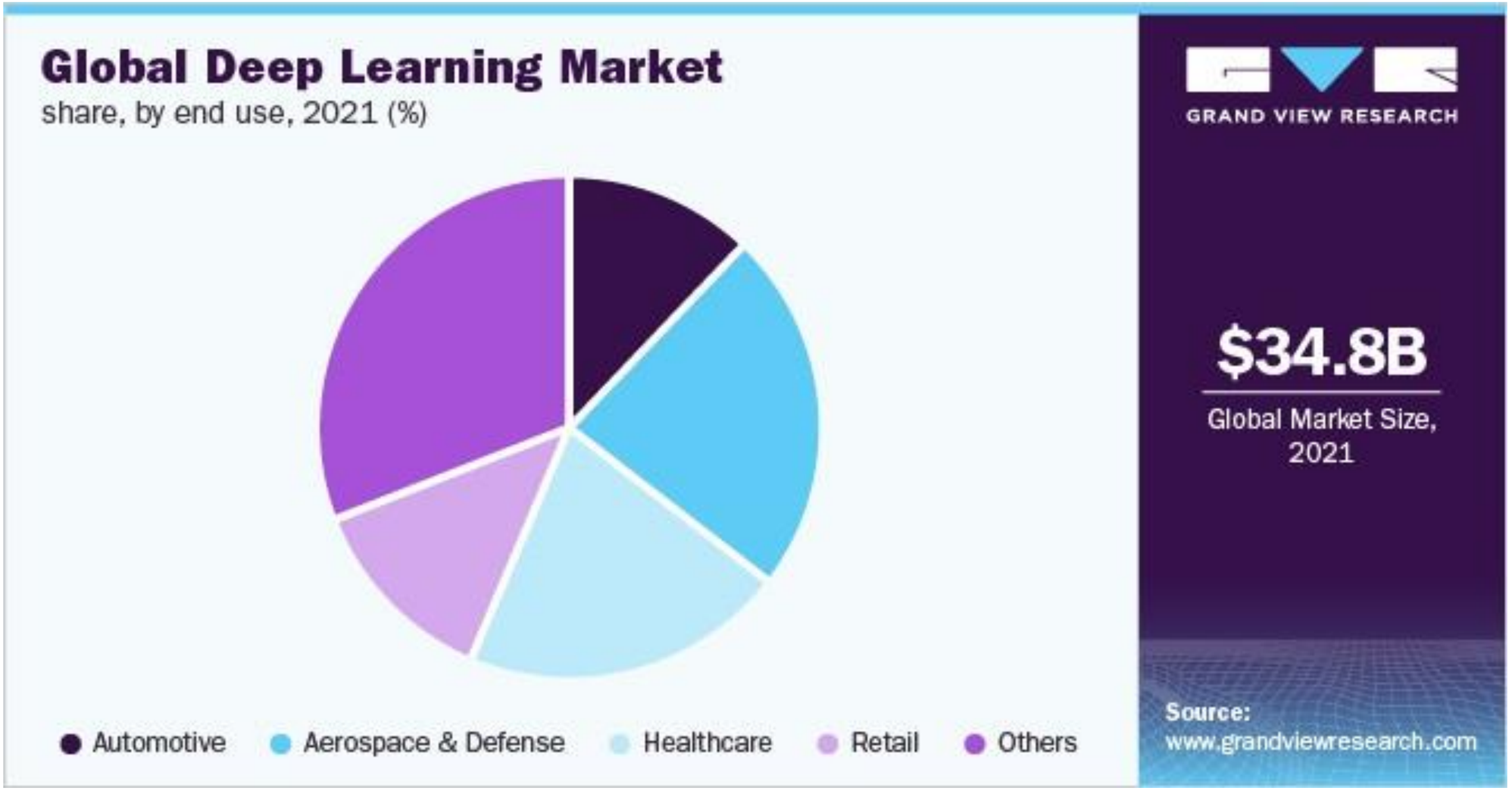
"Controlling Weather Field Synthesis Using Variational Autoencoders", Oliveira et al, ICML'21 Climate AI Workshop

Deep Learning Market



Revenue forecast in 2030 **USD 526.7 billion**

Deep Learning Market



Deep Learning Job Perspective

- Excellent Job Perspectives!
  - Automation requires ML/DL -> growth!
  - Top-notch companies are aggressively looking for you!
- Many industries now:
  - IT-Companies
  - Cars, Logistic, Health Care, etc... – Manufacturing / Robotics, etc...

But it is also challenging

- High-level understanding is not enough
  - Need proper theory background
  - Need proper practical skillsets
- Can be competitive!
  - Many people being trained
  - Downloading scripts / running code not enough :)
  - Deeper understanding often requires more intensive courses

Preliminary Syllabus

- Introduction to DL
- Convolutional Neural Networks
- Training CNNs
- Optimization of CNNs
- Generalization with CNNs
- CNN Architectures
- Semantic Segmentation
- Detection and Location
- Recurrent Neural Networks
- Generative Adversarial Networks
- Autoencoders
- Self-Supervised Learning

Lecture Structure

- Theory lectures

  Every Tuesdays 14:20-16:00

  - Interactive sessions - please don’t be shy!

- Practical sessions

  Every Thursdays 14:20-16:00

  - Explanatory part

  - Practical exercises

Grading System

- Programming Assignments (PA)
- One Written Examination (WE)
- 1 Final Project (PR): Paper + Presentation

- Final Grades:

  A1 = AVG(PA)
  A2 = (WE + PR) / 2

Infrastructure

- Zoom (for online classes)
- Google Colab
- E-Class

Office Hours

- Thursdays 11:00-13:00
- My room (505)

References

- Class slides
- Books:
  - Ian Goodfellow, Y. Bengio, A. Courvile, Deep Learning, MIT, 2016
  - Rajalingappaa Shanmugamani, Deep Learning for Computer Vision, 2018
  - Antonio Gulli, Sujit Pal, Deep Learning with Keras, 2017

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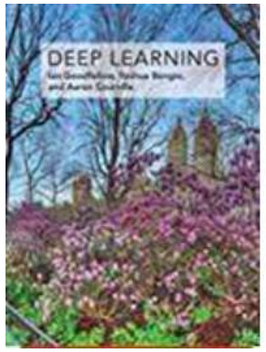

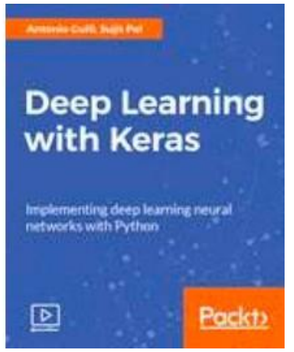

Next Lecture

Lecture 1

Introduction to Deep Learning

See you next class!